RESOURCE ALLOCATION FOR OFDM-BASED COGNITIVE RADIO SYSTEMS

A THESIS SUBMITTED IN PARTIAL FULFILLMENT

OF THE REQUIREMENTS FOR THE DEGREE OF

Master of Technology

In

Telematics and Signal Processing

By

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Roll No: 209EC1110

Department of Electronics & Communication Engineering

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Under the guidance of

Prof. Poonam Singh

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Dedicated to,

Shiva keshava

National Institute Of Technology

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CERTIFICATE

This is to certify that the thesis entitled, **"RESOURCE ALLOCATION FOR OFDM-BASED COGNITIVE RADIO SYSTEMS"** submitted by **VENKATA RAMA REDDY M (209EC1110)** in partial fulfillment of the requirements for the award of Master of Technology degree in Electronics and Communication Engineering with specialization in "Telematics and Signal Processing" during session 2010-2011 at National Institute of Technology, Rourkela (Deemed University) is an authentic work carried out by her under my supervision and guidance.

To the best of my knowledge, the matter embodied in the thesis has not been submitted to any other university/institute for the award of any Degree or Diploma.

DATE:

Prof. Poonam Singh

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VENKATA RAMA REDDY M

Abstract

Cognitive Radio (CR) is a novel concept for improving the utilization of the radio spectrum. It is a software controlled radio that senses the unused frequency spectrum at any time from the wide but congested wireless radio spectrum. This promises the efficient use of scarce radio resources. Orthogonal Frequency Division Multiplexing (OFDM) is a reliable transmission scheme for Cognitive Radio Systems [3] which provides flexibility in allocating the radio resources in dynamic environment. It also assures no mutual interference among the CR radio channels which are just adjacent to each other, making it one of the best schemes to be used in CR systems. Allocation of radio resources is a major challenge in cognitive radio systems. In a dynamic environment, many parameters and situations have to be considered which affect the total data rate of the system.

A Secondary users (CRUs/SUs) may coexist with the Primary user (PU) either on Conservative basis or on a more aggressive basis which allows secondary transmissions as long as the induced interference to the PU is below acceptable level. In this we have considered Uplink cognitive radio system heaving one PU coexists with M SUs and A Downlink of an Multi User Orthogonal Frequency Division Multiplexing CR system with one base station (BS) serving one PU and K SUs. We focused on the design on the design and analysis of subcarrier and power allocation scheme under imperfect CSI for cognitive OFDM systems. A two – step Algorithm for bit rate is proposed to obtain the (1) subcarrier allocation to secondary users and (2) bits, power allocation on subcarriers.

The algorithms attempt to maximize the total throughput of the CR system (secondary users) subject to the total power constraint of the CR system and tolerable interference from and to the licensed band (primary users).

Contents

List of Figures

Acronyms and abbreviations

FCC	Federal Communications Commission
CR	Cognitive Radio
DSA	Dynamic Spectrum Access
BPSK	Binary Phase Shift Keying
PU	Primary User
SUs	Secondary Users
QoS	*Quality of Service*
SDR	*Software Defined Radio*
DSS	Dynamic Spectrum Sharing
OFDM	Orthogonal Frequency Division Multiplexing
FPGA	*Field-programmable Gate Array*
AWGN	Additive White Gaussian Noise
CSI	Channel State Information
CBS	Cognitive Base Station
MU	Multi User
CRU	Cognitive Radio User

Chapter 1

INTRODUCTION

1.1. Cognitive Radio:

The electromagnetic radio spectrum is one of the most precious and scarce natural resource. Wireless networks today follow a fixed spectrum assignment strategy, the use of which is licensed by government agencies. This results in a large portion of assigned spectrum being used only intermittently or not at all due to various factors such as amount of traffic load on licensed users or geographical variations [1]. Actual measurements by FCC [2] support this fact by showing a severe underutilization of the licensed spectrum by the licensed or primary user (PU). Due to limited availability of radio spectrum and high inefficiency in its usage, new insights into the use of spectrum have challenged the traditional approaches to spectrum management. This necessitates a new communication paradigm to harness the underutilized wireless spectrum by accessing it opportunistically. This new communication technology is referred as Dynamic Spectrum Access (DSA) or Cognitive Radio (CR). Derived from J.Mitola's doctoral thesis [4], a cognitive radio is an intelligent wireless communication system that relies on opportunistic communication between unlicensed or secondary users (SU)s over temporarily unused spectral bands that are licensed to their PUs. The FCC suggests that any radio having adaptive spectrum awareness should be referred to as "Cognitive Radio" [5].

1.2. Cognitive Radio Features:

Cognitive Radio systems has been seen as a promising solution to improve the current spectrum underutilization while accommodating the increasing amount of services and applications in wireless networks [6]. Cognitive radio technology could potentially allow a complete SU system to simultaneously or opportunistically operate in the same frequency band as the PU. However, the development of cognitive radio is still at a conceptual stage due to a number of challenges it faces in how the it learns and adapts to the local spectral activity at each end of the link. The inherent feature of these CR systems would be their ability to recognize their communication environment and adapt the parameters of their communication scheme to maximize the quality of service (QoS) for the SUs while minimizing the interference to the PUs. Nevertheless, CR systems need to have a high degree of flexibility in order to overcome high variation in channel quality and interference. It will be build over software defined radio (SDR) due to implicit realization of these characteristics in SDR technology, which is already in production and is now available. The key features of CR transceivers are awareness of the radio environment (in terms of spectrum usage, power spectral density of transmitted/received signals), dynamic adaptability (adaptive tuning to system parameters such as transmit power, carrier frequency, modulation strategy etc.) and highly efficient cooperative or non-cooperative behavior (when there is competition between multiple CR transceivers).For a CR network to be deployed for practical usage a number of new technologies have to be developed. Of particular interest are the challenges involved in the design of physical and link layers. A number of new mechanisms within these layers such as measurement of network parameters, reliable spectrum sensing (detecting un used spectrum), spectrum mobility (maintaining seamless transition to a new spectrum), coexistence (with PUs and other CR networks), spectrum management, reliability (in terms of QoS), resource allocation (such as transmit power allocation and dynamic spectrum sharing (DSS)) and so on, have to be designed for most efficient and practically harmless access and sharing of opportunistic radio spectrum. In addition, it is critical to best optimize these mechanisms for different situations in order to enhance network performance. Since PU channels have to utilized by secondary users in a CR network without causing any degradation in service to PUs, Orthogonal Frequency Division Multiplexing (OFDM) has been identified as an potential transmission technology for future CR systems. This is mainly due to its great flexibility in dynamically changing spectral environments and allocating unused spectrum among SUs, which allows for simple adaptation of sub-carriers to fast changing conditions in radio spectrum. Besides, OFDM allows for multiuser diversity overcoming frequency selective fading which helps to enhance the spectrum utilization in general. A major challenge is to design efficient resource allocation algorithms (spectrum sharing and power allocation) that works well in OFDM based CR networks. In this thesis, we specifically look at these two problems of Sub Carrier Allocation, Bit Allocation and power allocation to CRUs and we then propose and design practical algorithms for them.

1.3. OFDM For Cognitive Radio:

OFDM stands for Orthogonal Frequency Division Multiplexing. It is the multi-carrier modulation technique in which data is split up into chunks and every chunk are modulated using closely spaced orthogonal subcarriers. The orthogonal subcarriers have the property that they do not have any mutual interference between them. So, this scheme is very useful for high bit-rate data communication.

One of the serious problems of high data rate transmission is time dispersion of pulses resulting in Inter-symbol Interference (ISI). In OFDM, the data is split into several low-rate data chunks and are modulated in overlapping orthogonal subcarriers. These splitting increases the symbol duration by the number of subcarriers used, thus reducing the ISI due to multipath.

OFDM is adapted as the best transmission scheme for Cognitive Radio systems [3]. The features and the ability of the OFDM system makes it fit for the CR based transmission system. OFDM provides spectral efficiency, which is most required for CR system. This is because the subcarriers are very closely spaced and are overlapping, with no interference. Another advantage of OFDM is that it is very flexible and adaptive. The subcarriers can be turned on and off according to the environment and can assist CR system dynamically. OFDM can be easily implemented using the Fast Fourier Transform (FFT), which can be done by digital signal processing using software.

We will discuss the several controls possible on the algorithm and the possible extension of this algorithm for multicarrier OFDM based CR systems. Traditional water-filling algorithm is inefficient for OFDM-CR networks due to the interaction with primary users (PU)s.

1.4. Motivation:

Enhancing spectrum efficiency and use is a significant task of regulatory authorities worldwide. A number of measurement studies of spectrum utilization have indicated that spectrum is sporadically used in many geographical areas and times. Low utilization and increased demand for the radio spectrum resource suggests the notion of secondary use, which allows unused parts of spectrum to become available temporarily for commercial purposes. The secondary use of spectrum is one of the promising ideas that can mitigate unsatisfied spectrum demand, potentially without major changes to incumbents. In this paper, we intend to outline the issues and discuss further study with the goal to determine what the necessary conditions are for spectrum sharing to be feasible.

We consider the basic elements of wireless communications that utilize radio spectrum space (signals and the channels) in our analysis. The signals and channels of potential interest are expected to exist in at least three dimensions: geographical space, time, and frequency. Different signals/channels occupy different subspaces, therefore allowing us to locate and distinguish one from another. The model provides useful graphical information to clarify the concerned topics at hands. This feasibility study of the secondary use takes several factors into consideration, including the availability of spectrum, interference, mobility, practicality of communications, and service applications.

Exploring the problems of providing secondary use of spectrum gives us the ability to consider basic obstacles to secondary use, including why primary users would allow secondary use and, equally important, under what circumstances secondary users might emerge. The reality of identifying the pre-conditions for secondary use is a crucial step towards higher level of efficient spectrum utilization.

1.5. Thesis Outline:

Following the introduction, the rest of the thesis is organized as follows:

Chapter 2: Literature survey on cognitive radio. Introduction to cognitive radio, cognition term, challenges, spectrum sensing, spectrum sharing.

Chapter 3: A Resource allocation in cognitive Orthogonal Frequency Division Multiplexing systems under channel state information .The channel gains are trained preamble assisted channel estimation. Sharing between one PU and M Cognitive Radio Users (Secondary Users) studied in two steps one is subcarrier allocation, and other step is bit power allocation.

Chapter 4: A Resource allocation in Multi User Orthogonal Frequency Division Multiplexing Systems Under Partial Cannel State Information.

Chapter 5: The work is concluded in this chapter and the future work is presented.

Finally at the end of the thesis References are included

Chapter 2

LITERATURE SURVEY

2.1. Introduction:

Cognitive radio has emerged as a promising technology for maximizing the utilization of the limited radio bandwidth while accommodating the increasing amount of services and applications in wireless networks. A cognitive radio (CR) transceiver is able to adapt to the dynamic radio environment and the network parameters to maximize the utilization of the limited radio resources while providing flexibility in wireless access. The key features of a CR transceiver are awareness of the radio environment (in terms of spectrum usage, power spectral density of transmitted /received signals, wireless protocol signaling) and intelligence. This intelligence is achieved through learning for adaptive tuning of system parameters such as transmit power, carrier frequency, and modulation strategy (at the physical layer), and higher-layer protocol parameters. Development of cognitive radio technology has to deal with technical and practical considerations (which are highly multidisciplinary) as well as regulatory requirements. There is an increasing interest on this technology among the researchers in both academia and industry and the spectrum policy makers. The key enabling techniques for cognitive radio networks (also referred to as dynamic spectrum access networks) are wideband signal processing techniques for digital radio, advanced wireless communications methods, artificial intelligence and machine learning techniques, and cognitive radio-aware adaptive wireless/mobile networking protocols[7].

A cognitive radio is an adaptive, multi-dimensionally aware, autonomous radio system that learns from its experiences to reason, plan, and decide future actions to meet user needs. Standards groups and regulatory bodies around the world are increasingly seeking new ways of using, allowing access to, or allocating spectrum. This was made clear during the SDR Forum’s Global Regulatory Summit on SDR and Cognitive Radio Technologies (June 2005), when standards, regulatory and other key stake holder representatives from around the world discussed their spectrum management challenges and goals, and the role of new technologies. This interest in developing new spectrum utilization technologies combined with both the introduction of SDR and the realization that machine learning can be applied to radios is creating intriguing possibilities for new and promising technologies such as cognitive radio. Cognitive Radio and Dynamic Spectrum Access represent two complementary developments that will refashion the world of wireless communication. A cognitive radio, by contrast, can use knowledge of radio technology and policy, representations of goals, and other contextual parameters.

2.2. Term Cognition:

In a way, it can be argued that cognitive radio draws its inspiration from cognitive science. The roots of cognitive science are intimately linked to two scientific meetings that were held in 1956:

• The Symposium on Information Theory, which was held at the Massachusetts Institute of Technology (MIT). That meeting was attended by leading authorities in the information and human sciences, including Allen Newell (computer scientist), the Nobel Laureate, Herbert Simon (political scientist and economist),and Noam Chomsky (linguist). As a result of that symposium, linguists began to theorize about language, which was to be found subsequently in the theory of computers: the language of information processing.

• The Dartmouth Conference, which was held at Dartmouth College, New Hampshire. The conference was attended by the founding fathers of artificial intelligence, namely, John McCarthy, Marvin Minsky and Allen Newel. The goal of this second meeting was to think about intelligent machines. The Dartmouth Conference was also attended by Frank Rosenblatt (psychologist), the founder of (artificial) neural networks. At the conference, Rosenblatt described a novel method for supervised learning, which he called the perceptron.2 However; interest in neural networks was short lived: in a monograph published in 1969, Minsky and Papert used mathematics to demonstrate that there are fundamental limits on what Rosenblatt's perceptron could compute. The Minsky–Papert monograph, coupled with a few other factors, contributed to the dampening of interest in neural networks in the 1970s. We had to wait for the pioneering contributions of John Hopfield on neurodynamic systems and Rumlehart, Hinton and Williams on supervised learning in the 1980s for the revival of research interest in neural networks.

In a book entitled "The Computer and the Mind," Johnson-Laird postulated the following tasks of a human mind:

• To perceive the world

• To learn, to remember and to control actions

• To think and create new ideas

• To control communication with others

• To create the experience of feelings, intentions and self-awareness

Johnson-Laird, a prominent psychologist and linguist, went on to argue that theories of the mind should be modeled in computational terms.

Much of what has been identified by Johnson-Laird as the mind's main tasks and their modeling in computation terms apply equally well to cognitive radio. Indeed, we can go on to offer the following definition for cognitive radio involving multiple users.

The cognitive radio network is an intelligent multiuser wireless communication system that embodies the following list of primary tasks:

• To perceive the radio environment (i.e., outside world) by empowering each user's receiver to sense the environment on continuous time

• To learn from the environment and adapt the performance of each transceiver to statistical variations in the incoming RF stimuli

• To facilitate communication between multiple users through cooperation in a self-organized manner

• To control the communication processes among competing users through the proper allocation of available resources

• To create the experience of intentions and self-awareness the primary objective of all these tasks, performed in real time, is twofold:

• To provide highly reliable communication for all users

• To facilitate efficient utilization of the radio spectrum in a fair-minded way

2.3. Why Cognitive Radio?

Based on software-defined radio (SDR) technology, cognitive radios are the product of a multidisciplinary effort involving experts in wireless networks, digital communications, systems engineering, artificial intelligence, and other fields. As a result of these activities, it is hoped that these systems can simultaneously respect the rights of the incumbent license holders while providing greater flexibility and access to spectrum. Given the demand for more bandwidth and the amount of underutilized spectrum, DSA (*Dynamic Spectrum Access*) networks employing cognitive radios are a solution that can revolutionize the telecommunications industry, significantly changing the way we use spectrum resources, and design wireless systems and services.

2.4. *When Will Cognitive Radio Happen?*

Full Cognitive Radios do not exist at the moment and are not likely to emerge until 2030, when fully flexible Software Defined Radio technologies and the intelligence required to exploit them cognitively can be practically implemented.

The main obstacle to realizing a Full Cognitive Radio is the challenge of making a truly cognitive device, or a machine with the ability to intelligently make decisions based on its own situational awareness. Cognitive science is in its infancy. At this stage it is impossible to tell when machine cognition will be realized: it could be 50 years, 100 years or perhaps not at all.

We expect basic intelligent reconfigurable CR prototypes to emerge within the next five years. Some devices available already have some elements of CR. (e.g. WRANs, WLANs, military follower jammers).

2.5. Back Ground Study:

Most of today’s radio systems are not aware of their radio spectrum environment and operate in a specific frequency band using a specific spectrum access system. Investigations of spectrum utilization indicate that not all the spectrum is used in space (geographic location) or time. A radio, therefore, that can sense and understand its local radio spectrum environment, to identify temporarily vacant spectrum and use it, has the potential to provide higher bandwidth services, increase spectrum efficiency and minimize the need for centralized spectrum management. This could be achieved by a radio that can make autonomous (and rapid) decisions about how it accesses spectrum. Cognitive radios have the potential to do this. Cognitive radios have the potential to jump in and out of un-used spectrum gaps to increase spectrum efficiency and provide wideband services. **In some locations and/or at some times of the day, 70 percent of the allocated spectrum may be sitting idle.** The FCC has recommended that significantly greater spectral efficiency could be realized by deploying wireless devices that can coexist with the licensed users.

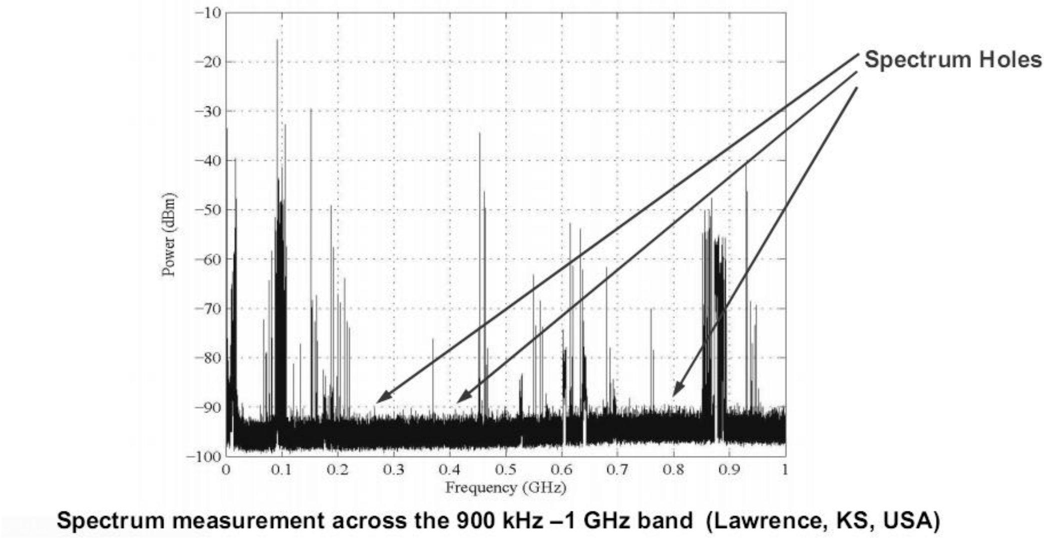

Figure 1. Spectrum Plot

Source: Cognitive Radio: A Flexible Wireless Platform for Transceiver Optimization by Alexander M. Wyglinski

A new class of radios was defined by the term cognitive radio. Several definitions (and variations) of Cognitive Radio exist:

- **Mitola -** ”Cognitive radio signifies a radio that employs model based reasoning to achieve a specified level of competence in radio related domains”.(1st time in 1999)
- **FCC -** ” A cognitive radio (CR) is a radio that can change its transmitter parameters based on interaction with the environment in which it operates”.

The idea of a Cognitive cycle for Cognitive Radio was first described by Mitola [8].

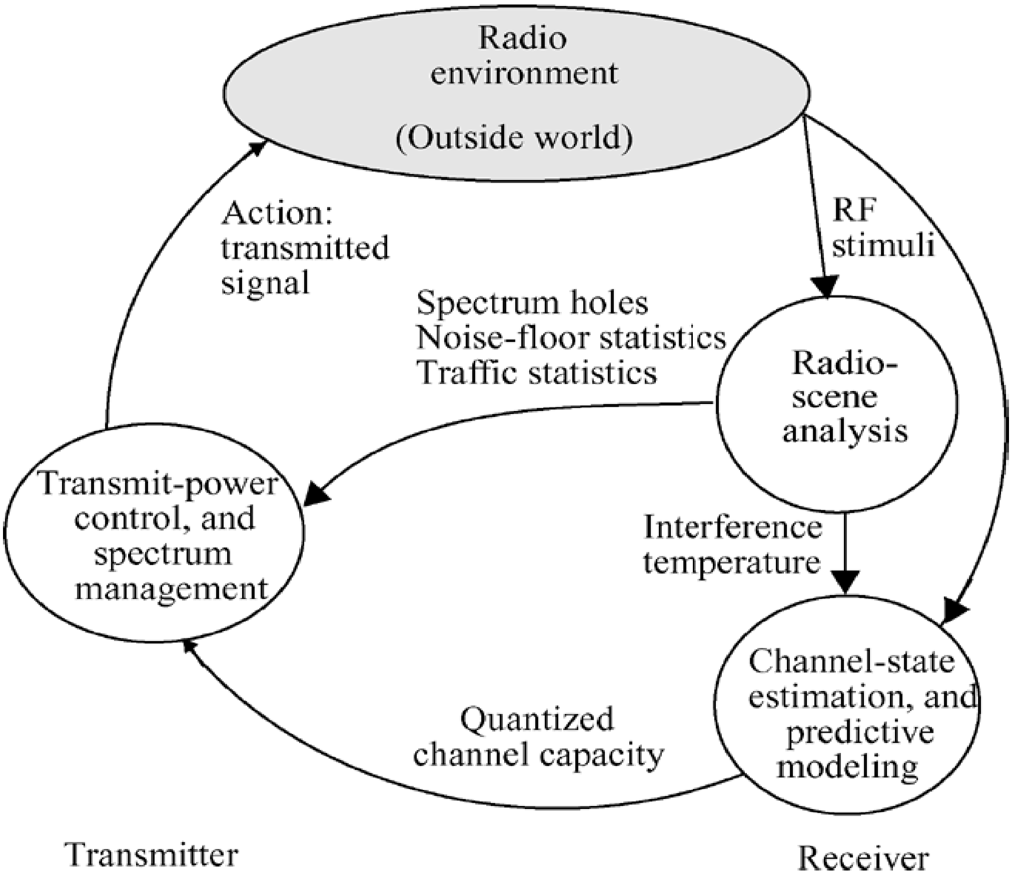

Figure 2. COGNITIVE CYCLE

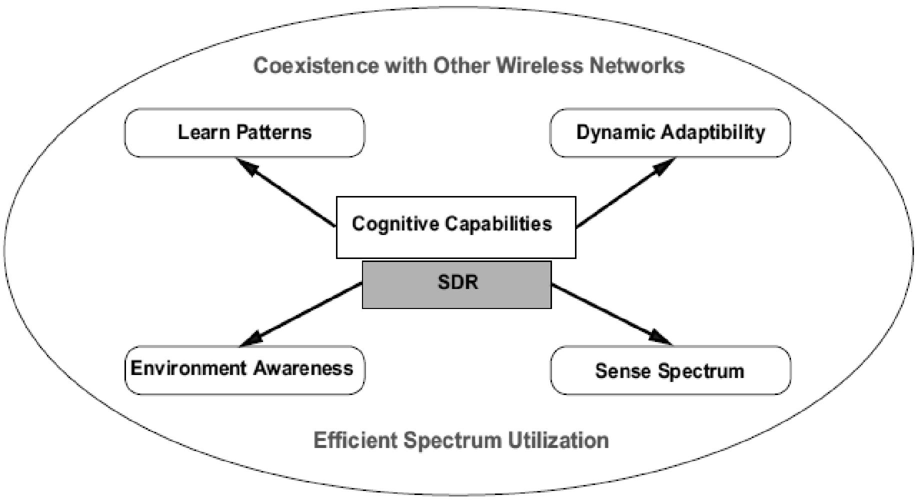

Figure 3. FUNCATIONALITIES OF TYPICAL COGNITIVE RADIO

Cognitive Radios represent the evolution of software defined radios (SDRs) into intelligent, operating environment aware and adaptive radios that promise reliable wireless communication as well as provide efficient sharing of the radio spectrum, above figure 2, depicts the basic functionalities of a cognitive radio [9].

2.6. Cognitive Radio Hardware Design Challenges:

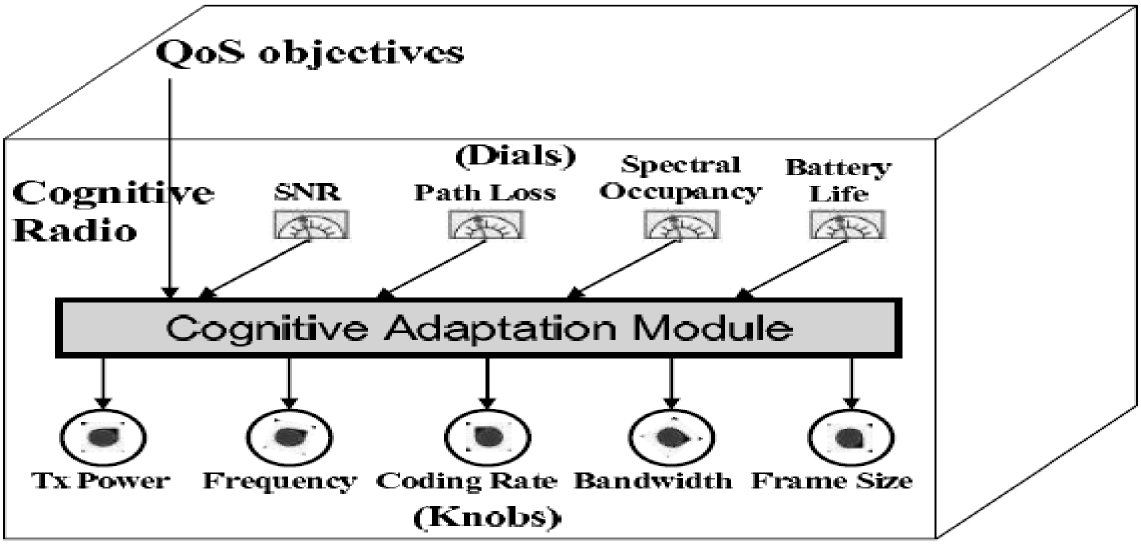

Figure 4. Visual Representation of Cognitive radio

The key challenge in the design of the physical architecture of a cognitive radio is the accurate and fast detection of weak signals over a wide frequency range of primary users when operating in licensed spectrum bands. In a typical cognitive radio device architecture, a wideband signal is received through a RF front-end and then sampled by a high speed analog-to-digital (A/D) converter [10]. The sampled digital output is then measured for the detection of primary user's signal. The RF front-end needs to be able to receive signals from various transmitters operating with different power levels, source coding techniques, bandwidths, etc. Thus, it must have the ability to quickly modify its parameters and detect even weak signals over a large and dynamic frequency range. Unfortunately, this requirement translates into using multi-GHz speed A/D converters, which may not always be feasible due to cost and other design limitations. Thus, various techniques are being explored by the research community to reduce the dynamic range of the signal to be sampled such as (i) filtering of strong signals using tunable notch filters and (ii) use of multiple antennae in conjunction with beam forming techniques to perform signal filtering in spatial domain rather than in the frequency domain.

The principal reconfigurable parameters that are incorporated in cognitive radios are:

- ***Operating frequency:*** Based on available radio spectrum information, the cognitive radio needs to be able to quickly change its operating frequency.
- ***Modulation techniques:*** A cognitive radio also may require to modify its source coding technique in order to be able to receive as well as transmit data to and from different radios operating on different protocols.
- ***Transmission power*:** Transmission power control provides an effective way of reducing interference to other users of a shared spectrum band and allows more users to share a spectrum.
- ***Communication stack:*** Based upon the need, it may be necessary for a cognitive radio to change its protocol stack for optimal data communication performance as well as for interoperability between various networks.

  Reconfigurability of operating parameters being an essential criterion in designing cognitive radios, most existing cognitive radios utilize an FPGA-based design rather than DSPs due to ease of programming. Most modern FPGAs usually come with highly optimized features implemented as non-standard configurable blocks (CLBs) like phase-locked loops, low voltage differential signal, clock data recovery, internal routing resources, hardware multipliers, memory, programmable I/O and microprocessor cores.

2.7. Possible Application:

CR techniques which allow spectrum sharing with other spectrum users are ideal for non-time critical applications. Four applications were considered to be the most promising:

- Mobile multimedia downloads (for example, download of music/video files to portable players) which require moderate data rates and near-ubiquitous coverage;
- Emergency communications services that require a moderate data rate and localized coverage (for example, video transmission from firemen’s’ helmets);
- Broadband wireless networking (for example, using nomadic laptops), which needs high data rates, but where users may be satisfied with localized “hot spot” services;
- Multimedia wireless networking services (e.g. audio/video distribution within homes) requiring high data rates.

The main specific benefit of full CR is that it would allow systems to use their spectrum sensing capabilities to optimize their access to and use of the spectrum. From a regulator’s perspective, dynamic spectrum access techniques using CR could minimize the burden of spectrum management whilst maximizing spectrum efficiency.

2.8. Spectrum Sensing in Cognitive Radio Networks:

Central to the ability to reconfigure operational parameters of cognitive radios is the ability to do spectrum sensing in order to identify spectrum holes that match the data transmission QoS requirements. Identification of spectrum holes suffers from the well-known problems of exposed and hidden (primary user) nodes [9].

To avoid interference and performance degradation of primary users in the TV band, the 802.22 working group has set $-116\ dBm$ as the sensitivity level for detecting whether a particular channel is free or not. While this might prevent interference to television receivers from unfortunately faded cognitive radios, the -116 dBm rule leaves little spectrum in the TV band open to detection and utilization by cognitive radios. Various studies have shown that the spectrum utilization in time and space is far lower than what would actually be possible because of the $-116\ dBm$ restriction. it was observed in that on an average 56% of the TV band channels are free in Midwest US, only 22% can be recovered on an average by the $-116\ dBm$ rule. Typically, in most locations, channels with signal strength above the $-116\ dBm$ limit will still be safe to use for a large majority of the cognitive radios not experiencing any unfortunate fading.

The basic hypothesis problem for transmitter detection is usually formulated as:

$$x(t) = \begin{cases} n(t) & H_{0,} \\ h.S(t) + n(t) & H_1 \end{cases} \quad \textbf{(1)}$$

Where $x(t)$is the signal received by the cognitive radio, $S(t)$ is the transmitted signal of the primary user, $n(t)$ is the additive white gaussian noise (AWGN), and h is the amplitude gain of the channel. $H_0$is the null hypothesis for the scenario that there is no primary user on the channel. H_1 is the alternative hypothesis that there exists a primary user currently transmitting on the channel. In general, by increasing the amount of time (up to a certain extent) for which the test statistics is averaged, the hypothesis can be tested arbitrarily well. However, there exists an SNR wall, below which a detector will fail to be robust, no matter how long it can observe the channel. A survey of the literature reveals that three schemes are generally utilized for transmitter detection using the above hypothesis model in Equation (1). They are matched filter-based, energy-based, and feature –based detection. We provide below a description of these various schemes.

(1) ***Matched filter based detection:*** When the nature of the primary user's signal is known a priori, the matched filter is the optimal detector for stationary AWGN as it maximizes the received SNR. The cognitive radio requires to know the modulation type, pulse shape, and the packet format (in case of digital transmission) of the primary user. Considering the fact that most primary users have a fixed transmission scheme with well-defined pilot, preamble, synchronization word or spreading codes, coherent detection using matched filter thus offers a useful way of spectrum hole detection in real-life scenarios.

(2) ***Energy-based detection:*** In scenarios where not enough information about the primary's signal is known, the optimal detector can be the energy detector which requires knowledge of only the AWGN power. In this scheme, the received signal at the CR is passed through a band pass filter, squared and then integrated over the observation interval. The output of the integrator is then compared to a threshold value to detect the presence of a licensed user. Because of the ease of implementation and ability to adjust to varying primary user transmission types, most recent works on primary transmitter detection have adopted the energy detector. Several recent works attempt to build more sophisticated energy based detectors that incorporates shadowing and multipath fading factors.

The main drawbacks of the energy-based detection method are:

• Susceptibility to the uncertainties—both spatial and temporal, in noise power and

• Inability to differentiate between various signal types and identify specific features in the received signal. Thus, often times it is difficult to ascertain whether the received signal at the CR is from a primary user or from another secondary user

(3) ***Cyclostationary-based feature detection:*** Cyclostationary- based feature detection techniques attempt to take advantage of the fact that most modulated signals are in general coupled with sine wave carriers, pulse trains, repeated spreading, hopping sequences, or cyclic prefixes, which lead to inherent periodicity in the received signal. Such modulated signals are characterized as Cyclostationary since their mean and autocorrelation exhibit periodicity. The features are detected by analyzing a spectral correlation function.

The wireless device measures RF energy in the channel or the received signal strength indicator to determine whether the channel is idle or not. But this approach has a problem in that wireless devices can only sense the presence of a primary if and only if the energy detected is above a certain threshold. It is true that one cannot arbitrary lower the threshold as this would result in non-detection because of the presence of noise. In the feature detection approach, which has been used in the military to detect the presence of weak signals, the wireless device uses cyclostationary signal processing to detect the presence of primaries. If a signal exhibits strong cyclostationary properties, it can be detected at very low signal-to-noise ratios (SNR) .Some have proposed sensing method to identify PU by estimating their radio frequency (RF) transmission parameters. The identification is done by matching the a priori information about PU transmission parameters to the features extracted from the received signal. In other techniques show a PU detection technique exploiting the local oscillator (LO) leakage power emitted by the RF front end of primary receivers. A blind sensing algorithm based on oversampling the received signal or by employing multiple receives antennas. This method does not require any information of PU signal or channel. The proposed method combines linear prediction and QR decomposition of the received signal matrix. Two signal statistics are computed from the oversampled received signal. The ratio of these two statistics indicates the presence/absence of the PU signal.

2.9. Spectrum Sharing in Cognitive Radio Systems:

One of the main challenges in open spectrum usage is the spectrum sharing. Spectrum sharing can be regarded to be similar to generic medium access control (MAC) problems in existing systems. However, as we will investigate in this section, substantially different challenges exist for spectrum sharing in networks. The coexistence with licensed users and the wide range of available spectrum are two of the main reasons for these unique challenges. In this section, we delve into the specific challenges for spectrum sharing in systems , overview the existing solutions and discuss open research areas.

Chapter 3

COGNITIVE OFDM SYSTEMS UNDER IMPERFECT CSI WITH SMART CHANNEL ESTIMATION

3.1. Introduction:

Cognitive radio (CR) employing OFDM has drawn many interests in designing efficient radio resource allocation schemes. Most of the existing works considered the cognitive scenario under perfect knowledge of system state, such as channel state information (CSI). However, it is serious to properly regulate the interference caused by secondary users (SUs) to each primary user (PU)[11].

Here, we focus on the design and analysis of subcarrier and power allocation scheme under imperfect CSI for cognitive OFDM systems. A smart way using training preamble is presented to obtain the CSI of Rayleigh block-fading channel between the transmitter and receiver. During the training phase, the receiver estimates the channel and feeds the estimate back to the transmitter.

During the transmission phase, a two-step algorithm for capacity maximization is done to obtain the subcarrier assignment and power allocation for each SU. However, in all cases publications are done by assuming the perfect channel state information (CSI). Yet, perfect CSI is difficult to obtain in real cognitive systems. As a result, it is important to take into account of the effects of the imperfect CSI in the design of radio resource allocation algorithm for CR systems.

We focused on the design and analysis of subcarrier and transmit power allocation schemes under imperfect CSI with channel estimation for cognitive OFDM systems. During the estimation phase, we introduce a smart way that is based on the training preamble to perform channel estimate at the cognitive base station (CBS), which estimates the channel and feeds the estimate information back to SUs.

Then during the data transmission phase, we propose an efficient scheme for capacity maximization that employs different algorithms to perform subcarrier and power allocation in two steps.

3.2. System Model and Problem:

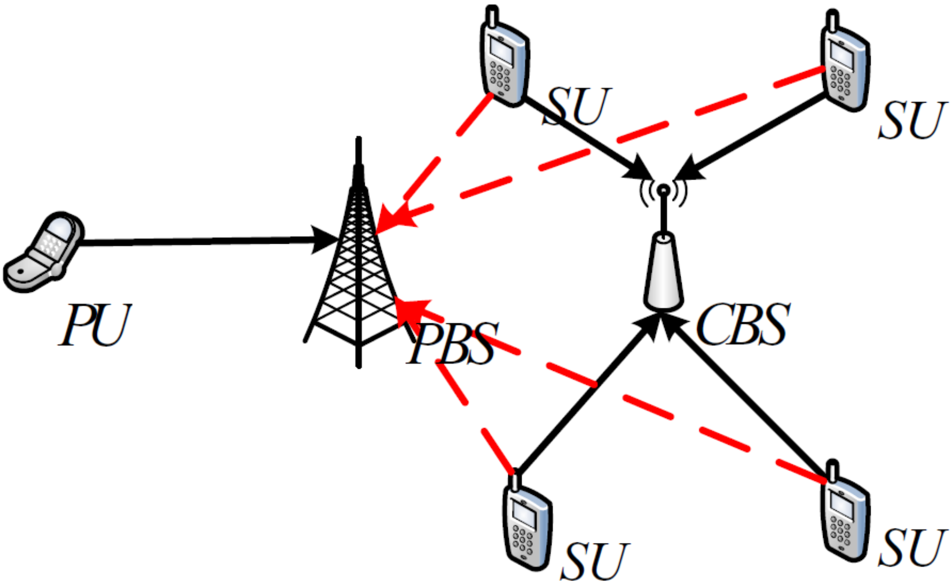

Figure 5. Uplink CR system one PU with M SUs

3.2.1. System model:

We consider an uplink cognitive radio system, where a PU coexists with M SUs. All the SUs are covered by the same cognitive base station (CBS).The shared wireless channel we consider in this paper is a flat Rayleigh block-fading channel, and we assume that the channel changes slowly so that the channel gains will be constant during transmission. The shared spectrum band BHz is divided into N orthogonal subcarriers, and each with a bandwidth of $\frac{B}{N}Hz$. The subcarrier bandwidth is assumed to be much smaller than the coherence bandwidth of the wireless channel.

As no subcarrier can support the transmissions for more than one CR in OFDM-based systems, we have

$$\sum_{m=1}^{M} a_{m,n} \leq 1, \forall n = 1,2, \dots, N.$$

As depicted above, the achievable Shannon`s rate R_m of each SU m is computed as:

$$R_m = \sum_{n=1}^{N} a_{m,n}\, r_{m,n}$$

$$= \sum_{n=1}^{N} a_{m,n} \times \frac{B}{N} \times \log_2\left(1 + \frac{h_{m,n}P_{m,n}}{\Gamma I_{m,n}}\right) \qquad (1)$$

Where,

$r_{m,n}$ is the transmit rate of SU m on Subcarrier n ,

$h_{m,n}$ is the channel gain of SUm on subcarrier n ,

$P_{m,n}$ is the transmit power of SU m on subcarrier n ,

$I_{m,n}$ is the noise plus interference power experienced by SU m on Subcarrier n .

And

Γ is a constant signal-to-noise ratio (SNR) gap relevant to the required bit error rate

BER_{req} [12]:

$$\Gamma = -\frac{\ln(5BER_{req})}{1.5} \qquad (2)$$

3.2.2. Problem Formulation:

As mentioned above, the subcarrier and power allocation for capacity maximization can be expressed mathematically:

$$\max_{a_{m,n}\, P_{m,n}} \sum_{m=1}^{M} R_m$$

Such that.,

$$\sum_{m=1}^{M} a_{m,n} \le 1, \forall n = 1,2, \dots, N. \tag{3}$$

$$\sum_{n=1}^{N} P_{m,n} \le P_{max}^{m}, \forall m = 1,2, \dots, M .$$

$$P_{m,n} + I_{m,,n} \le P_{th}$$

$$P_{m,n} > 0$$

Where,

P_{max}^{m} is the power budget of SU m ,

P_{th} is the permissible interference power level of PU.

Most existing works assume that $h_{m,n}$ is perfectly known. However, $h_{m,n}$ is imperfect, which is an important scenario for CR systems. Thus, in the following sections, we first introduce a smart way to obtain the instant CSI, and then propose a two-step algorithm for the capacity maximization problem (3).

3.3. Training Preamble Assisted Channel Estimation:

We consider a smart way using training preamble [13] to perform channel estimate at the CBS, which estimates the channel and feeds the estimate information back to SUs. Then the CBS could use this information in the proposed radio resource allocation algorithms, and send the subcarrier and power allocation information to SUs through control channels. Suppose each block of OFDM symbols comprises of $T \ge 1$training symbols, i.e.,$s(1), s(2), \dots \dots, s(T),$ which are used to probe the channel.

Then the received signals corresponding to these training symbols are**:**

$$y(i) = Hs(i) + n(i),\ i = 1,2, \ldots . T \tag{4}$$

Where n is zero-mean, unit variance, circularly symmetric, complex, Gaussian noise. It is assumed that the transmitted symbols have unit power, i.e., $E\{|s|^2\} = 1$.

Denote

$$Y = [y(1), y(2), \ldots \ldots \ldots \ldots \ldots . y(T)]$$

$$S\ =\ [s(1), s(2), \ldots \ldots \ldots \ldots \ldots . s(T)]$$ and

$$N\ =\ [n(1), n(2), \ldots \ldots \ldots \ldots . n(T)].$$

Then the maximum likelihood estimate of $h_{m,n}$ is given by:

$$\hat{H} = \arg\ min\,\|Y - HS\|^2 = YS^H(SS^H)^{-1} \tag{5}$$

According to [13], the channel estimates $\hat{h}_{m,n}$ computed using (5) with orthogonal training symbols are statistically independent Gaussian variable with**:**

$$\hat{h}_{m,n} \quad N(h_{m,n}, \frac{1}{T}) \tag{6}$$

3.4. Proposed Allocation Scheme:

As the capacity maximization problem in (3) under multiple constraints is generally very hard to solve because of the uncertain variables $a_{m,n}$ and the continuous variables $P_{m,n}$. Therefore, we separate (3) as two sub-problems in the following sections.

3.4.1. Greedy Subcarrier Allocation:

We present a greedy subcarrier allocation algorithm, which fully assigns $SU\ m$ channels with the best gains. Details of the subcarrier allocation algorithm are described as follows**:**

1. Initialization

$$\text{Set } a_{m,n} = 0 \quad \forall m, n$$

2. Subcarrier Allocation for n=0 to N

$$n = \arg\max_{n\in\{1,\dots,N\}} |h_{m,n}|$$

$$a_{m,n} = 1.$$

Then we can get the number N_m of subcarriers allocated to SU m.

3.4.2. Fast Iterative Water-Filling:

Power allocation for each SU starts sequentially after subcarrier allocation. In this section, we will propose a fast power allocation algorithm with additional interference power constraint under consideration based on the water-filling algorithm in [14]. As we know, there is a power allocation which is the solution to the optimization problem defined in (3) and it is of the form:

$$P_{m,n} = \Gamma I_{m,n}\left[\lambda_m - \frac{1}{h_{m,n}}\right]^+ \tag{7}$$

Where $[x]^+\ max(x, 0)$ and λ_m is the water filling level of SU. By replacing (7) into (1), we get**:**

$$r_{m,n} = B\left[\log_2(\lambda_m P_{m,n}\ )\right]^+ \tag{8}$$

Then we round off (8) to make $r_{m,n}$ be an integer number for practical modulation / demodulation:

$$\hat{r}_{m,n} = \left[r_{m,n}\right] \tag{9}$$

Where [ ] indicates the rounding function.

The followings are the summary of the proposed Power allocation algorithm:

1. Initialize λ_m as

$$\lambda_m = \frac{1}{N_m}\left(\frac{P_{max}^m}{\Gamma I_{m,n}} + \sum_{n=1}^{N} \frac{a_{m,n}}{h_{m,n}}\right),$$

And give a specific value for $0 < \mu < 1$

2. While $(\sum_{n=1}^{N} P_{m,n} \geq P_{max}^m \qquad P_{m,n} + I_{m,,n} \leq P_{th})$

3. For m=1to M

Calculate (7), (9);

If $\hat{r}_{m,n} = 0, N_m = N_m - 1;$

Update λ_m as

$$\lambda_m \leftarrow \lambda_m - \mu \frac{1}{N_m} . \frac{1}{\Gamma I_{m,n}} \left| P_{max}^m - \sum_{n=1}^{N} P_{m,n} \right|.$$

3.5. Complexity Analysis:

For all SUs, each iteration of the classic water filling has an $O(MN\log_2 N)$ complexity, but our proposed algorithm has an $O(N)$ complexity in each iteration. So the total complexity of our scheme is greatly reduced, and the required iterations of our scheme can be adjusted by μ.

3.6. Simulation and Results:

Simulation results are presented in this section to demonstrate the effectiveness of our subcarrier and power allocation algorithms presented in the previous sections. We consider a practical network, where a centralized BS of the CR network is accessed by multiple SUs with located in the coverage area.

The Simulation Parameters used are

- Number of Secondary Users (SUs) $(M) = 15\sim25,$
- Band Width of Shared spectrum $(B) = 3.2\ MHz,$
- Number of subcarriers $(N) = 32,$
- Required bit error rate $(BER_{req}) = 10^{-3},$
- Noise plus interference $(I_{m,n}) = 0.01\sim 0.1\ mW,$
- Power budget of SU $m(P_{max}^{m}) = 0 \sim 50\ mW,$
- Permissible interference of PU $(P_{th}) = 10\ mW,$
- Channel gain $(h_{m,n}) = 0.1\sim1$
- Step size (μ)=0.3
- All channels are Rayleigh distributed random variables with mean = 1

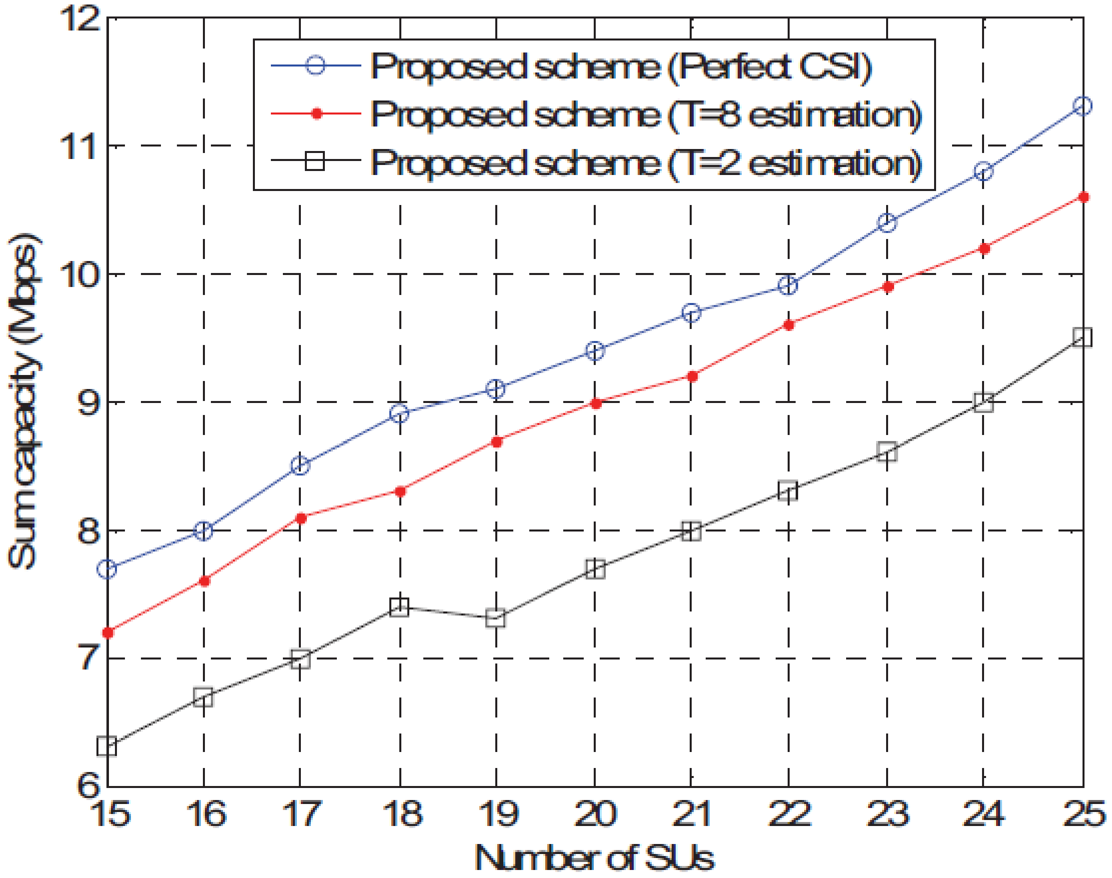

Figure 6.Comparison of Sum Capacity Under Different number of SUs

From above graph we can observe that when we are using a larger number of training symbols $(i.e., T = 8)$ our proposed scheme under training preamble assisted estimation can achieve higher sum capacity. This is because a larger number of training symbols yield smaller channel estimation errors, and thus the estimation is approximate to practical link gains. Contrarily, less training symbols that yield larger estimation errors lead to unsuitable subcarrier allocation, so producing a bad performance on sum capacity.

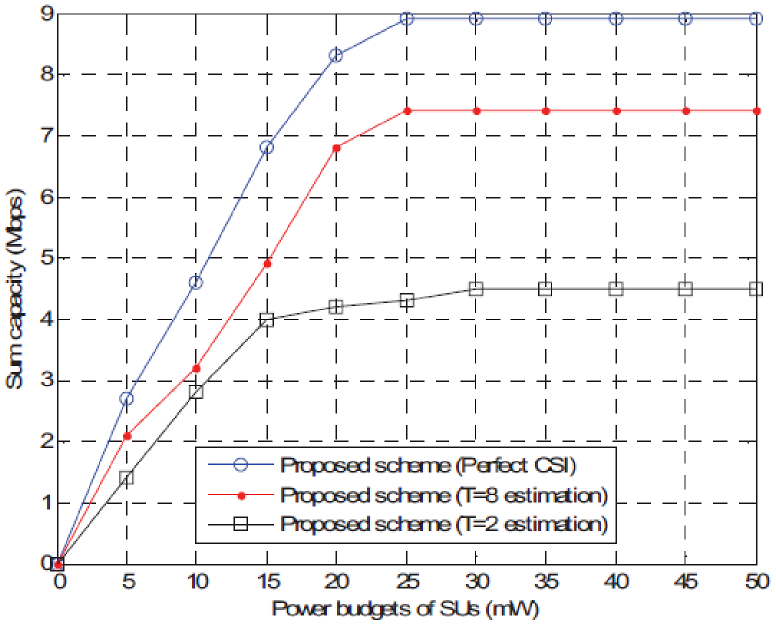

Figure 7.Comparison of sum capacity under different power budgets of SUs

From the above graph we can observe that the power budget (P_{max}^{m}) of the 20 SUs are increased, the sum capacity keeps increasing until the interference power on any sub carrier exceeds $10mW$ (P_{th}).

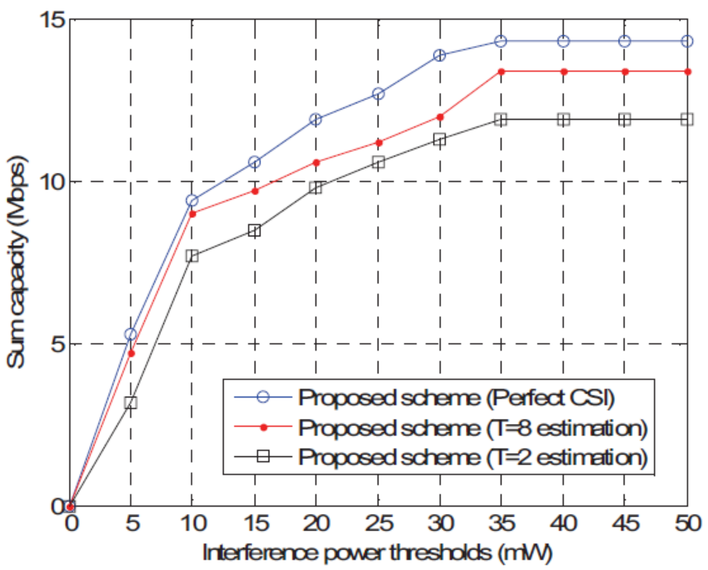

Figure 8.Comparison of Sum Capacity Under Different Power thresholds of PU

From the above graph we have observed that moreover, sum capacity increases as the interference power thresholds of PU are increased, until the power budgets of the 20 SUs are exhausted.

Chapter 4

MU-OFDM BASED COGNITIVE RADIO SYSTEMS UNDER PARTIAL CSI

4.1. Introduction:

In performance analyses of wireless communication systems, it is often assumed that perfect channel state information (CSI) is available at the transmitter. This assumption is often not valid due to channel estimation errors and/or feedback delays. To ensure that the system can satisfy target quality of service (QoS) requirements, a careful analysis which takes into account imperfect CSI is required. Orthogonal frequency division multiplexing (OFDM) is a modulation scheme which is attractive for use in a CR system due to its flexibility in allocating resources among CRUs. The problem of optimal allocation of subcarriers, bits, and transmit powers among users in a multiuser-(MU-) OFDM system is a complex combinatorial optimization problem. In order to reduce the computational complexity, the problem is solved in two steps by many suboptimal algorithms**:** (1) determine the allocation of subcarriers to users and (2) determine the allocation of bits and transmit powers to subcarriers [15]. The resource allocation in MU-OFDM based CR systems based on Partial Channel State Information. Assumption the CSI is acquired perfectly at the CRUs and is feed back to the BS with delay Td seconds. The Channel experiences frequency selective fading and Doppler Shift Relying on Partial CSI, we maximize the total data rate while maintaining a prescribed (BER) for a fixed transmit power and mutual interference .we analyze the impact of partial CSI on the wireless transmission.

4.2. System Model:

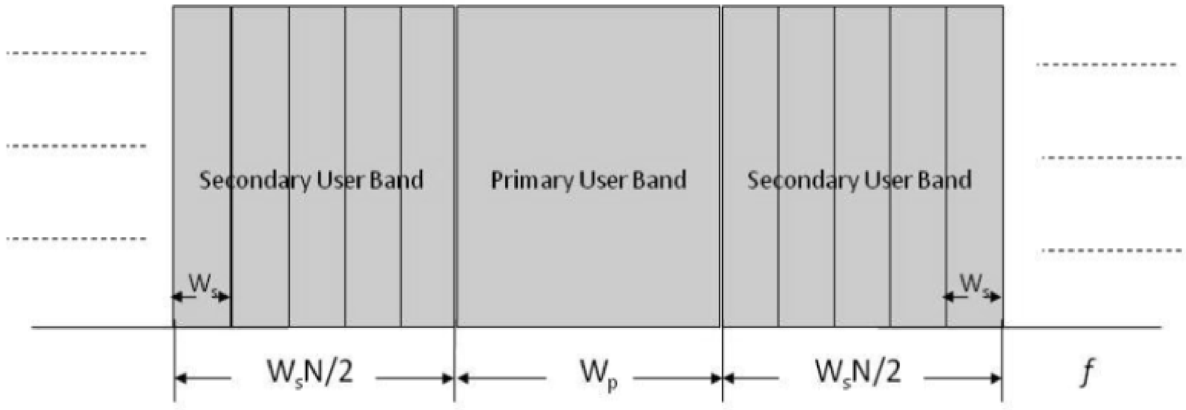

Figure 9.Primary User band of Width Wp and Secondary user sub-bands, each of width Ws.

We consider an Down-link Multi User OFDM cognitive radio system with ONE base station (BS) serving 1PU and K CRUs. The basic model in [16] is summarized here for our convenience. The PU channel is Wp Hz wide and the bandwidth of each OFDM subchannel is Ws Hz. On either side of the PU channel, there are $N/2$ OFDM subchannels. The PU band width is surround on each side by $N/2$ subcarriers with each subcarrier occupying a band of width Ws Hz. The subcarriers are used for transmission to the secondary users using OFDM. As the BS can transmit simultaneously to the both primary and secondary users, the primary user`s signal can cause interference to the secondary users and vice-versa. The BS has only partial CSI and allocates subcarriers, transmit powers, and bits to the CRUs once every OFDM symbol period. The channel gain of each subcarrier is assumed to be constant during an OFDM symbol duration.

The power spectral density (PSD) of the nth subcarrier signal is assumed to have the

$$\Phi_n(f) = P_n T_s \left(\frac{\sin \pi f T_s}{\pi f T_s}\right)^2$$

WhereP_n denotes the subcarrier n transmit signal power and T_s is the symbol duration.

On the either side of the PU channel, there are $N/2$ OFDM subchannels .the BS has only partial CSI and allocates subcarriers, transmit powers, and bits to the CRU1s once every OFDM symbol period. The channel assumed to be constant during OFDM symbol duration.

Suppose that Pn is the transmit power allocated on subcarrier n and g_n is the channel gain of subcarrier n from the BS to the PU.

The resulting interference power spilling into the PU channel is given by

$$I_n(d_n, P_n) = P_n . IF_n \tag{1}$$

Where,

$$IF_n \triangleq \int_{d_n - W_p/2}^{d_n + W_p/2} |g_n|^2 \Phi_n(f) df \tag{2}$$

represents the interference factor for subcarrier$n$, d_n is the spectral distance between the center frequency of subcarrier n and that of the PU channel, and $\Phi_n(f)$ denotes the normalized baseband power spectral density (PSD) of each subcarrier.

Let h_{nk} be the channel gain of subcarrier n from the BS to CRU k, and let$\Phi_{RR}(f)$ be the baseband PSD of the PU signal.

The interference power to CRU k on subcarrier n is given by

$$S_{nk}(d_n) = \int_{d_n - W_s/2}^{d_n + W_s/2} |h_{nk}|^2 \Phi_{RR}(f) df \tag{3}$$

LetP_{nk} denote the transmit power allocated to CRU k on subcarrier$n$. For QAM modulation, an approximation for the BER on subcarrier n of CRU k is [17]

$$BER\ [n] \approx 0.2\ exp\left(\frac{-1.5\ |h_{nk}|^2 P_{nk}}{(2^{b_{nk}} - 1)(N_o W_s + S_{nk})}\right), \tag{4}$$

Where N_o is the one-sided noise PSD and S_{nk} is given by (3). Rearranging (4), the maximum number of bits per OFDM symbol period that can be transmitted on this subcarrier is given by

$$b_{nk} = \left\lfloor \log_2 \left(1 + \frac{|h_{nk}|^2 P_{nk}}{\Gamma(N_o W_s + S_{nk})}\right)\right\rfloor, \tag{5}$$

Where,

$\Gamma \triangleq -\ln(5BER[n])/1.5$ and $\lfloor . \rfloor$ denotes the floor function.

Equation (4) shows the relationship between the transmit power and the number of bits loaded on the subcarrier for a given BER requirement when perfect CSI is available at the transmitter. We now establish an analogous relationship when only partial CSI is available.

The imperfect CSI that is available to the BS is modeled as follows. We assume that perfect CSI is available at the receiver. The channel gain, h_{nk}, for subcarrier n and CRU k is the outcome of an independent complex Gaussian random variable, that is, $H_{nk} \sim \mathcal{CN}(0, {\sigma_h}^2)$[18] , corresponding to Rayleigh fading. For clarity, we will denote random variables and their outcomes by uppercase and lowercase letters, respectively.

For notational simplicity, we will use h to denote an arbitrary channel gainh_{nk}. The BS receives the CSI after a feedback delay $\tau_d = dT_s$where T_s is the OFDM symbol duration. We assume that the noise on the feedback link is negligible. Suppose that h_f is the channel gain information that is received at the BS, then $h_f(t) = h(t - \tau_d)$.

From [19], The correlation between H and H_f is given by

$$E\{HH_f^H\} = \rho {\sigma_h}^2, \tag{6}$$

Where, the correlation coefficient, ρ, is given by

$$\rho = J_o(2\pi f_d dT_s) \tag{7}$$

Represent the correlation coefficient by Jake`s model, In (6) and (7), $J_o(\cdot)$ denotes the zeroth-order Bessel function of the first kind, f_d is the Doppler frequency, $E\{\cdot\}$ is the expectation operator, andH_f^H denotes the complex conjugate of H_f .

The minimum mean square error (MMSE) estimator of H based on $H_f = h_f$ is given by [20],

$$\overline{H} = E\{H|\, H_f = h_f\} = \rho h_f \,. \tag{8}$$

The transmitter obtain an unbiased channel estimate h based on partial CSI received from the receiver through the feedback channel; before update feedback arrives, the transmitter treats h as deterministic, and in order to account for CSI imperfections , it relies on an estimate of the true channel h , which is formed as

From (6), the actual gain can be written as [21] follows

$$h = \overline{H} + \epsilon, \tag{9}$$

Where,$\epsilon \sim \mathcal{CN}(0, \sigma_\in{}^2)$, with $\sigma_\in{}^2 = \sigma_h{}^2(1 - |\rho|^2)$.

The transmitter treats h as deterministic and updates its value when the next feedback becomes available.

4.3. Multi User Resource Allocation Problem Formulation:

Based on the partial CSI available at the BS, we wish to maximize the total CRU transmission rate while maintaining a target BER performance on each subcarrier and satisfying PU interference and total BS CRU transmit power constraints. Let $\overline{BER}[\mathrm{n}]$ denote the average BER on subcarrier$n$, and let $\overline{BER_o}$ represent the prescribed target BER, that can be different from subcarrier.

Therefore, we can formulate constrained optimization problem as follows:

$$max\, R_s \triangleq w_s \sum_{n=1}^{N} \sum_{k=1}^{K} a_{nk} b_{nk}, \qquad (10)$$

Subject to

$$\overline{BER}[\mathrm{n}] \leq \overline{BER_o}\ , \qquad \forall n \qquad (11)$$

$$\sum_{k=1}^{K} \sum_{n=1}^{N} a_{nk} P_{nk} \leq P_{total}, \qquad (12)$$

$$P_{nk} \geq 0, \qquad \forall n,\mathrm{k} \qquad (13)$$

$$\sum_{k=1}^{K} \sum_{n=1}^{N} a_{nk} P_{nk} IF_n \leq I_{total}, \qquad (14)$$

$$\sum_{k=1}^{K} a_{nk} \leq 1, \qquad \forall n \qquad (15)$$

$$a_{nk} \in \{0,1\}, \qquad \forall n, k \qquad (16)$$

Let $a_{nk} \in \{0,1\}$ be a subcarrier allocation indicator function, i.e.,, $a_{nk} = 1$ if and only if subcarrier n is allocated to user k. To avoid excessive interference among CRUs, it is assumed that each subcarrier can be used for transmission to at most CRU at any given time.

$$R_1 : R_2 : \dots \dots \dots : R_K = \lambda_1 : \lambda_2 : \dots \dots \dots . : \lambda_K, \qquad (17)$$

Where P_{total} is the total power budget for all CRUs, I_{total} is the maximum interference power that can be tolerated by the PU, and the λ_k term represents the nominal bit rate weight (NBRW) for CRU k, and

$$R_k = w_s \sum_{n=1}^{N} a_{nk} b_{nk,} \qquad \forall k = 1,2, \dots , K. \qquad (18)$$

Denotes the total bit rate achieved by CRU k^{th} . Constraint (11) ensures that the average BER for each subcarrier is below the given BER target. In equalities (12),(13)&(14) correspond to the power and interference constraints, respectively. In equality (15) reflects the condition that any given subcarrier can be allocated to at most one user (17) reflects the proportional fair among CRU`s.

When ignoring inequality (11), it is easy to drive the relationship between transmit power and bits .However, we can`t derive the relationship between directly from inequality (11).We solve the expectation of $\overline{BER}[\mathrm{n}]$ first. Suppose the n^{th}subcarrier is allocated to k^{th} CRU.

Constraint (11) ensures that the average BER for each subcarrier is below the given BER target. Constraint (12) states that the total power allocated to all CRUs cannot exceedP_{total}, while constraint (14) ensures that the interference power to the PU is maintained below an acceptable levelI_{total}. Constraints (15) result from the assumption that each subcarrier can be assigned to at most one CRU. Constraint (17) ensures that the bit rate achieved by a CRU Satisfies a proportional fairness condition.

Based on (9), we calculated the average of the right hand side (RHS) of (4), treating h_{nk} as an outcome of an independent complex Gaussian Variable. For an arbitrary vector

$\propto \sim \mathcal{CN}(\mu, \Sigma)$,

We have the following:

$$E\{\exp\left(-\propto^{H}\propto\right)\} = \frac{\exp\left(-\mu^{H}(1+\Sigma)^{-1}\mu\right)}{\det\left(1+\Sigma\right)}, \tag{19}$$

Where **I** denotes the identity matrix. Applying (19) to (4), we obtain

$$\overline{BER}[\mathrm{n}] \approx 0.2\ \frac{1}{1+\Psi_{\sigma_{\epsilon}}{}^{2}}\, exp\left(-\frac{\Psi|\overline{H}_{nk}|^{2}}{1+\Psi_{\sigma_{\epsilon}}{}^{2}}\right), \tag{20}$$

Where$\overline{H}_{nk} = \rho h_{nk}^{f}$, $\quad \Psi \approx \frac{1.5\ P_{nk}}{\{(2^{b_{nk}}-1)(N_{o}W_{s}+S_{nk})\}}$, and h_{nk}^{f} denotes the channel gain that is feedback to the BS.

From (20), an explicit relationship between minimum transmit power and number of transmitted bits cannot be easily derived. However, since $\overline{BER}[\text{n}]$ in (20) is a monotonically decreasing function of P_{nk}, we obtain the minimum power requirement while satisfying the constraint in (11) by setting $\overline{BER}[\text{n}] \leq \overline{BER_o}$ .We now derive a simpler, albeit approximate, relationship between the required transmit power, $\overline{BER}$, and the number of loaded bits.

When setting, $\mathcal{K}_\mu = {|\overline{H}_{nk}|^2}/{\sigma_\in{}^2}$, $r = 1.5\ P_{nk}/(N_o W_s + S_{nk})$,$g = 1/\left(2^{b_{nk}} - 1\right)$,and

$\bar{\gamma} = \left(1 + \mathcal{K}_\mu\right)\sigma_\in{}^2 r$, the RHS of (20) has the from

$$I_\mu(\bar{\gamma}, g, \theta) = \frac{(1+\mathcal{K}_\mu)sin^2\theta}{(1+\mathcal{K}_\mu)sin^2\theta + g\bar{\gamma}} exp\left(-\frac{\mathcal{K}_\mu g\bar{\gamma}}{(1+\mathcal{K}_\mu)sin^2\theta + g\bar{\gamma}}\right), \tag{21}$$

With $\theta = \pi/2$ .the function $I_\mu(\bar{\gamma}, g, \theta)$ is Rician distributed with Rician distributed with Rician factor $\mathcal{K}_\mu$[21] .A Rician distribution with $\mathcal{K}_\mu$ can be approximate by a Nakagami m distribution [22] as follows:

$$\widetilde{I_\mu}(\bar{\gamma}, g, \theta) = \left(1 + \frac{g\bar{\gamma}}{m_\mu sin^2\theta}\right)^{-m_\mu}, \tag{22}$$

With $\theta = \pi/2$, where$m_\mu = \left(1 + \mathcal{K}_\mu\right)^2/\left(1 + 2\mathcal{K}_\mu\right)$. Therefore, we approximate the RHS of (20) by

$$\overline{BER}[\text{n}] \approx 0.2\ \left(1 + \frac{(\sigma_\in{}^2 + |\bar{h}_{nk}|^2)\Psi}{m_\mu}\right)^{-m_\mu}. \tag{23}$$

Then, from (23), we obtain

$$P_{nk} \approx \frac{\left((5\overline{BER}[\text{n}])^{-(1/m_\mu)} - 1\right)m_\mu}{\sigma_\in{}^2 + |\bar{h}_{nk}|^2} .\gamma\ , \tag{24}$$

Where, $\gamma = (2^{b_{nk}} - 1)(N_o W_s + S_{nk})/1.5$, from (24), we obtain

The maximum number of bits in a symbol transmitted on this subcarrier n is set to

$$b_{nk} = \left\lfloor \log_2 \left(1 + \frac{({\sigma_\epsilon}^2 + |\bar{h}_{nk}|^2) P_{nk}}{\Gamma'(N_o W_s + S_{nk})}\right) \right\rfloor , \tag{25}$$

Where,

$$\Gamma' = \left((5\overline{BER_o})^{-(1/m_\mu)} - 1\right) m_\mu / 1.5 \, .$$

4. 4. Resource Allocation with Partial CSI:

Clearly, the objective function in equation (10) is an optimization problem with two levels, (i.e., determine the subcarrier allocation indicator a_{nk} and transmit bits b_{nk} .Note that the joint subcarrier, bit, and power allocation problem in (10)–(17) belongs to the mixed integer nonlinear programming (MINP) class [23]. For brevity, we use the term "bit allocation" to denote both bit and power allocation. Since the optimization problem in (10)–(17) is generally computationally complex, we first use a suboptimal algorithm, which is based on a greedy approach, to solve the subcarrier allocation problem in Section 4.4.1. After subcarriers are allocated to CRUs, we apply a memetic algorithm (MA) to solve the bit allocation problem in Section 4.4.2.

4.4.1. Subcarrier Allocation:

From (17), it can be seen that the subcarrier allocation depends not only on the channel gains, but also on the number of bits allocated to each subcarrier. Moreover, allocation of subcarriers close to the PU band should be avoided in order to reduce the interference power to the PU to a tolerable level. First, we set a threshold to delete some worst subcarriers for all users. For the remaining $\widehat{N}$ subcarriers, we assume that each user experiences a channel factor. Therefore, we use a threshold scheme to select subcarriers for CRUs.

Suppose that $\widehat{N}$ subcarriers are available for allocating to CRUs. We assume equal transmit power for each subcarrier.

Let,

$$\Psi_k \approx \frac{1}{\hat{N}} \sum_{n=1}^{\hat{N}} \frac{(|\bar{H}_{nk}|^2 + \sigma_\epsilon{}^2)}{\Gamma'(N_o W_s + S_{nk})}, \ \forall k = 1,2, \dots, K \quad (26)$$

$$\overline{IF} = \frac{1}{\hat{N}} \sum_{n=1}^{\hat{N}} IF_n. \quad (27)$$

If a subcarrier is assigned to CRU k, the maximum number of bits which can be loaded on the subcarrier is given by

$$b_k = min\left(\left\lfloor \log_2\left(1 + \frac{\Psi_k P_{total}}{\hat{N}}\right)\right\rfloor, \left\lfloor \log_2\left(1 + \frac{\Psi_k I_{total}}{\hat{N}\,\overline{IF}}\right)\right\rfloor\right), \ \forall k = 1,2, \dots, K \quad (28)$$

Using (26)–(28), we can determine the number of subcarriers assigned to each CRU as follows. Let m_k be the number of subcarriers allocated to CRU k. Assuming that the same number of bits is loaded on every subcarrier assigned to a given CRU, the objective in (10) is equivalent to finding a set of $\{m_1, m_2, \dots\dots, m_K\}$ subcarriers to maximize

$$max\, R_s \triangleq w_s \sum_{k=1}^{K} m_k b_k, \quad (29)$$

Subject to

$$m_1 b_1 : m_2 b_2 : \dots\dots\dots : m_K b_K = \lambda_1 : \lambda_2 : \dots\dots\dots : \lambda_K, \quad (30)$$

$$P \leq P_{total}, \quad (31)$$

$$I \leq I_{total}, \quad (32)$$

Where P is the total transmit power allocated to all subcarriers and I is the total interference power experienced by the PU due to CRU signals. The subcarrier allocation problem in (29)–(32) can be solved using the SA algorithm proposed in [24]. Note that we need to make use of (24) in the SA algorithm if only partial CSI is available. A pseudocode listing for the SA algorithm is shown in Pseudocode 1. The algorithm has a relatively low computational complexity $O(KN)$. After subcarriers are allocated to CRUs, we then determine the number, b_n, of bits allocated to subcarrier n

Algorithm: SA

for n=1 to number of subcarriers **do**

find $k^* \in \{1,2,\ldots,K\}$ which maximizes $(|\bar{H}_{nk}|^2 + \sigma_\epsilon{}^2)/\left(\Gamma'(N_o W_s + S_{nk})\right)$;

Using (b_{nk}), calculate the number of bits loaded on Subcarrier

n as b_{nk^*} with P_{nk^*}=P_{total}/N;

initialize $\widehat{N}$ to 0;

if $b_{nk^*} > 2$ **then**

subcarrier n is available; increment $\widehat{N}$ by 1;

else

subcarrier n is not available;

end if

end for

For each $k \in \{1,2,\ldots,K\}$, initialize the number, m_k , of subcarriers allocated to CRU k to 0

calculate b_k ;

for $n = 1$ to $\widehat{N}$ **do**

find the value, η, of $k \in \{1,2,\ldots,K\}$ which minimizes $m_k b_k/\lambda_k$;

allocate subcarrier n to CRU η;

Increment m_η by one.

end for

Pseudocode 1: Pseudocode for subcarrier allocation algorithm.

4.4.2. Bits Allocation:

We can assign the subcarriers to the cognitive radio users .Now, after subcarrier allocation, we have to do is Bit allocation and Power allocation. Here we are denoting bit allocation to both bit and power allocation. This Combinatorial Optimization Problems is solved by using Memetic Algorithm (MA).

The Performance of Memetic Algorithm Highly depends (dependent) on the parameter settings.

Appropriate Local search (LS) and Genetic Operators selection will obtain solutions close to the global optimal solution quickly. To select good LS and genetic Operators for our problem, some important properties of it should be analyzed. Fitness landscape is an powerful technique for analyzing, the behavior of combinatorial Optimization problems.

Memetic algorithms (Mas) are evolutionary algorithms which have been shown to be more efficient than standard genetic algorithms (Gas) for many combinatorial optimization problems [25–27]. Using (24), the bit allocation problem can be solved using the MA algorithm proposed in [24]. It should be noted that the chosen genetic operators and local search methods greatly influence the performance of Mas. The selection of these parameters for the given optimization problem is based on the results in [24]. A pseudocode listing of the proposed memetic algorithm is shown in pseudocode 2.

Algorithm: MA
$Initialize\ Population\ P$; $\{Input: X_i = \left[x_{i1},\ x_{i2}, \dots \dots \dots, x_{iN}\right]$,
$i = 1,2, \dots., pop\_size\}$
$P = Local\_Search(P)$;
for $i = 1$ to $Number\_of\_Generatio$ **do**
$S = selectForVariation(P)$;
S′=crossover(S);
$S' = Local\_Search(S')$;
$add\ S'\ to\ P$;
$S'' = muation(S)$;
$S'' = Local\_Search(S'')$;
$add\ S''\ to\ P$;
$P = selectForSurvival(P)$;
end for
return P. $\{Output: X_i = \left[x_{i1}, x_{i2}, \dots \dots \dots x_{iN}\right]$, $i = 1,2, \dots., pop\_size\}$

Pseudocode 2: Pseudocode for the memetic algorithm.

The roles of mutation, Inbreeding, Cross Breeding and Selection in evolution. Bi parental reproduction as a factor in evolution .Properties of gene mutation. Species natural selection. The total number of genes in the cell of higher Organisms ranges from 1000 up.

Let X_i be the chromosome of member i in a population, expressed as

$$X_i = [x_{i1}\ x_{i2} \ldots \ldots \ldots x_{iN}\ ], \quad \forall i = 1,2, \ldots ., pop\_size, \tag{33}$$

Where pop_size denotes the population size. The initial integer solution vectors are randomly created with in the region of admissible solutions. A brief description of the MA algorithm in [24] is now provided.

(1) **The *select* For *Variation*** function selects a set, $S = \{s_1, , s_2, \ldots, s_{pop\_size}\}$, of chromosomes from P in a roulette wheel fashion, that is, selection with replacement.

(2) **Crossover:** suppose that. $S = \{Y_1, , Y_2, \ldots, Y_{pop\_size}\}$. Let P_{cross}denote the crossover probability, and let $u_i, i = 1, 2, \ldots, pop\_size,$ denote the outcome of an independent random variable which is uniformly distributed in $[0, 1]$, then $Y_i$is selected as a candidate for crossover if and only if $u_i \le P_{cross}$, $i = 1, 2, \ldots, pop\_size$. Suppose that we have n_c such candidates, we then form $n_c/2$ disjoint pairs of candidates (parents).

For each pair of parents Y_i and Y_j

$$Y_i = [y_{i1}\ \ y_{i2} \ldots \ldots\ \cdots\ y_{ip}\ \ y_{i(p+1)} \cdots\ y_{iN}]\ ,$$

$$Y_j = [y_{j1}\ \ y_{j2} \ldots \ldots\ \cdots\ y_{jp}\ \ y_{j(p+1)} \cdots\ y_{jN}]\,. \tag{34}$$

We first generate a random integer $p \in [1, N - 1]$, using one cut point crossover operator to swap the two parents, to obtain two children as follows:

$$Y_i{}' = [y_{i1}\ \ y_{i2} \ldots \ldots\ \cdots\ y_{ip}\ \ y_{i(p+1)} \cdots\ y_{iN}]\ ,$$

$$Y_j{}' = [y_{j1}\ \ y_{j2} \ldots \ldots\ \cdots\ y_{jp}\ \ y_{j(p+1)} \cdots\ y_{jN}]\,. \tag{35}$$

(3) **Mutation:** let P_{mutation}denote the mutation probability. For each chromosome in S, we generate $u_i, i = 1,2, \ldots \ldots N$,where u_i denotes the outcome of an independent random variable which is uniformly distributed in [0, 1]. Then for each component i for which $u_i \leq P_{\text{mutation}}$, we substitute the value with a randomly chosen admissible value.

(4) **Selection of surviving chromosomes:** we select the pop_size chromosomes of parents and off springs with the best fitness values as input for the next generation.

4.5. simulation Results:

In the simulation, the parameters of the MA algorithm were chosen as follows: population size, pop_size = 40; number of generations = 20; crossover probability, P_{cross} = 0.05; mutation probability, P_{mutation}= 0.7. We consider a system with one PU and K = 4 CRUs. The total available bandwidth for CRUs is 5MHz and supports 16 subcarriers with W_s= 0.3125 MHz. we assume that W_p= W_s and an OFDM symbol duration, of T_s of 4μs. In order to understand the impact of the fair bit rate constraint in (17) on the total bit rate, three cases of user bit rate requirements with λ = [1 1 1 1], [1 1 1 4], [1 1 1 8] were considered. In addition, three cases of partial CSI with ρ =1, 0.9 and 0.7 were studied. It is assumed that the subcarrier gains h_{nk} and, g_k for $n \in \{1,2,\ldots,N\}, k \in \{1,2,\ldots,K\}$ are outcomes of independent identically distributed $(i.i.d.)$ Rayleigh-distributed random variables (rvs) with mean square value$E(|\bar{H}_{nk}|^2) = E(|G_k|^2) = 1$. The additive white Gaussian noise (AWGN) PSD, N_0, was set to 10^{-8} W/Hz. The PSD, Φ_{RR} , of the PU signal was assumed to be that of an elliptically filtered white noise process. The total CRU bit rate,R_s, results were obtained by averaging over 10,000 channel realizations. The 95% confidence intervals for the simulatedR_s, results are within ±1% of the average values shown.

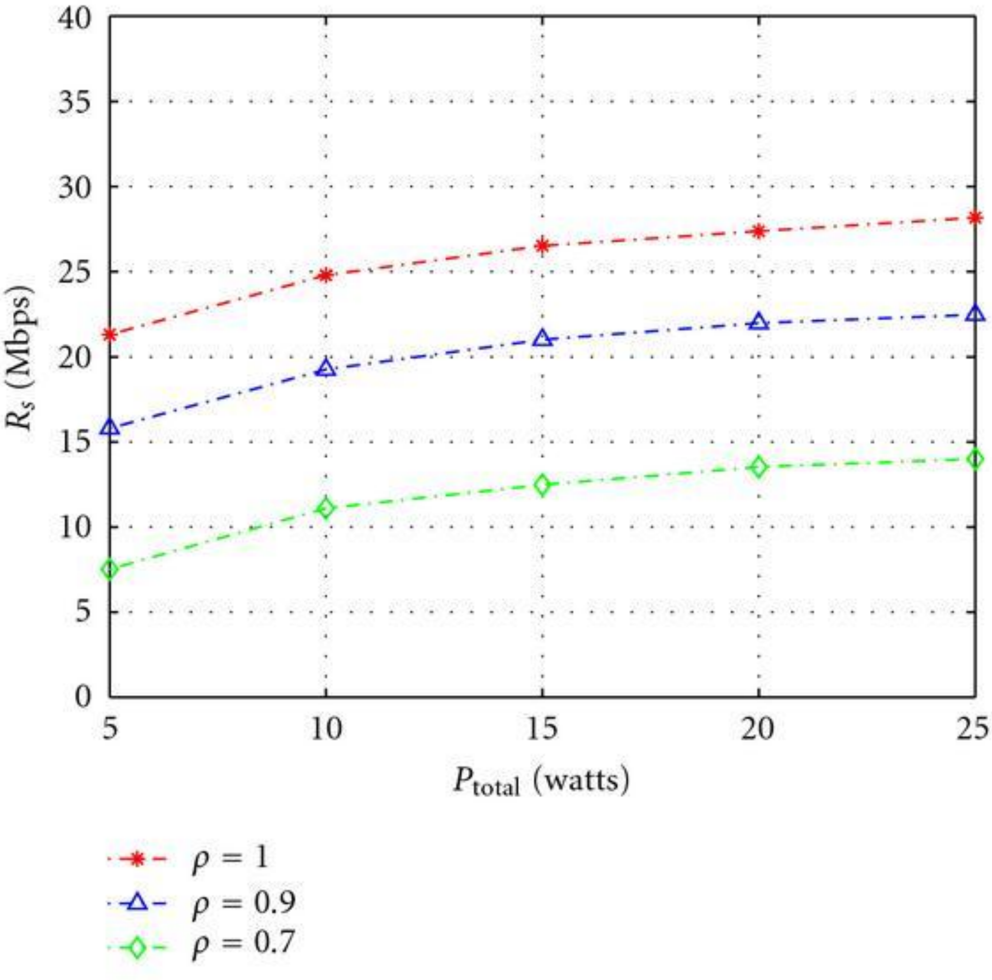

Figure 10. Average total CRU Rs Vs total CRU transmit power for λ= [1 1 1 1] with different ρ

The above graph shows the average total bit rate, R_s , as a function of the total CRU transmit power, P_{total} , for ρ = 0.7, 0.9, and 1 with $\boldsymbol{\lambda}$ = [1 1 1 1], I_{total} = 0.02 W, and a PU transmit power, P_m, of 5W. As expected, the average total bit rate increases with the maximum transmit power budgetP_{total}. It can be seen that the average total bit rate, R_s, varies greatly with ρ .

AT P_{total} = 5W, R_s increases by a factor of 2 as ρ increases from 0.7 to 0.9. This illustrates the big impact that inaccurate CSI may have on system performance. TheR_s, curves level off asP_{total} increases due to the fixed value of the maximum interference power that can be tolerated by the PU

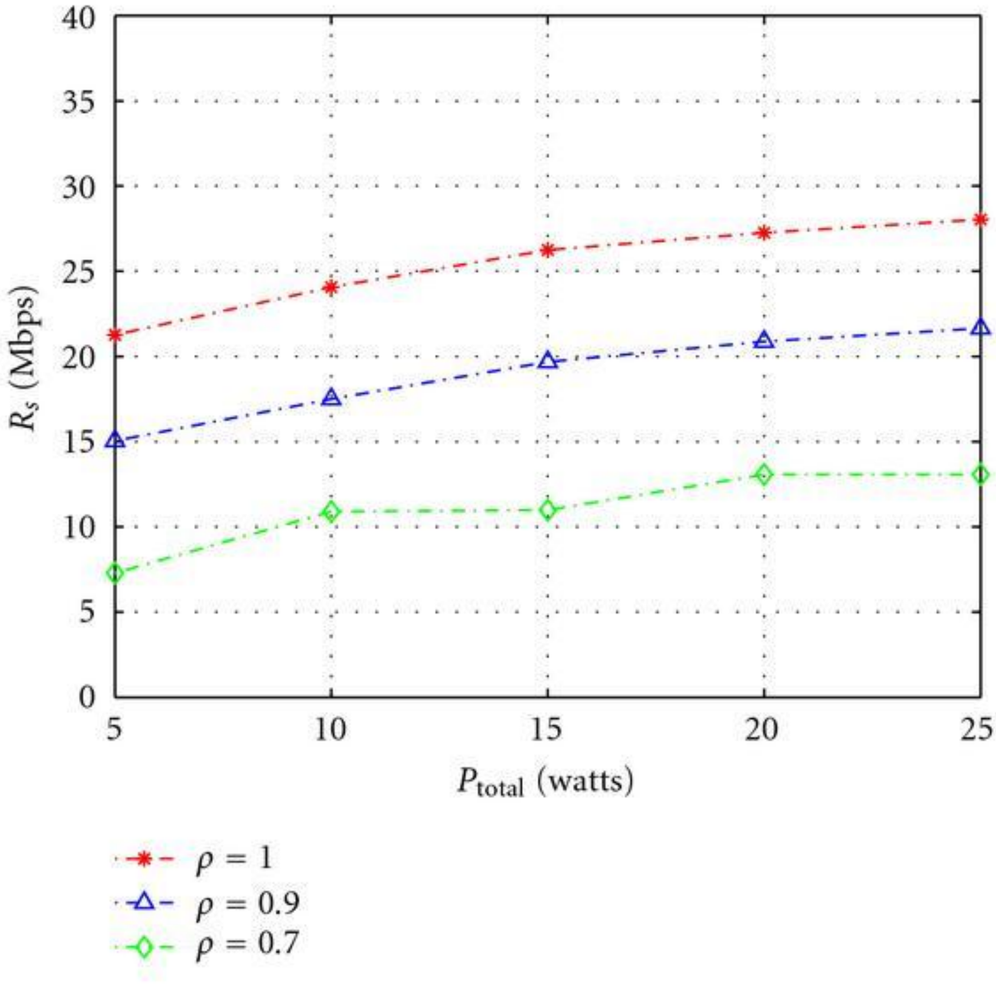

Figure 11.Average total CRU Rs Vs total CRU transmit power for λ= [1 1 1 4] with different ρ

The above graph shows the average total bit rate, R_s, as a function of the total CRU transmit power, P_{total}, for ρ = 0.7, 0.9, and 1 with $\boldsymbol{\lambda}$ = [1 1 1 4], I_{total} = 0.02 W, and a PU transmit power, P_m, of 5W. As expected, the average total bit rate increases with the maximum transmit power budget P_{total}. It can be seen that the average total bit rate, R_s, varies greatly with ρ .

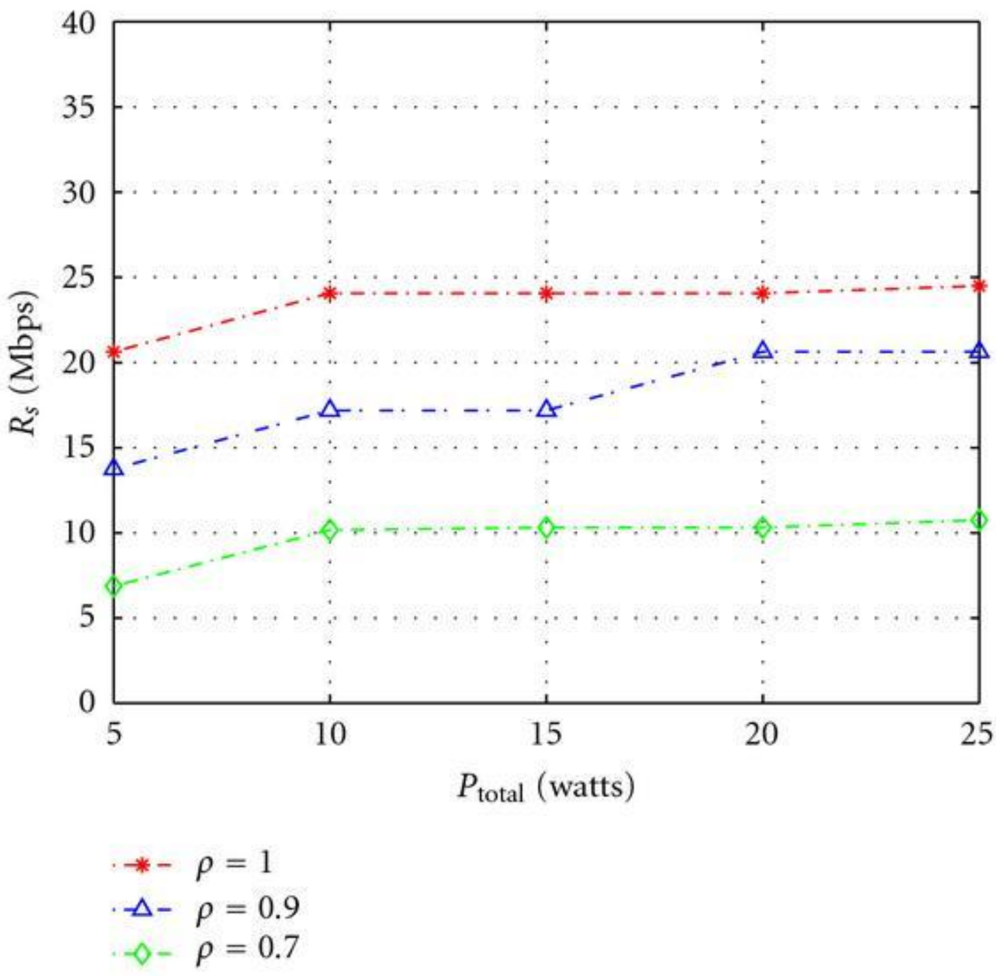

Figure 12.Average total CRU Rs Vs total CRU transmit power for λ= [1 1 1 8] with different ρ

The above graph shows the average total bit rate, R_s, as a function of the total CRU transmit power, P_{total} , for ρ = 0.7, 0.9, and 1 with $\boldsymbol{\lambda}$ = [1 1 1 8], I_{total}= 0.02 W, and a PU transmit power, P_m, of 5W. As expected, the average total bit rate increases with the maximum transmit power budgetP_{total}. It can be seen that the average total bit rate, R_s, varies greatly with ρ .

Corresponding results for $\boldsymbol{\lambda}$ = [1 1 1 4] and $\boldsymbol{\lambda}$ = [1 1 1 8] are plotted in Figures 2 and 3, respectively. The Average total bit rate, R_s, decreases as the NBRW distribution becomes less uniform; the reduction tends to increase with P_{total}.

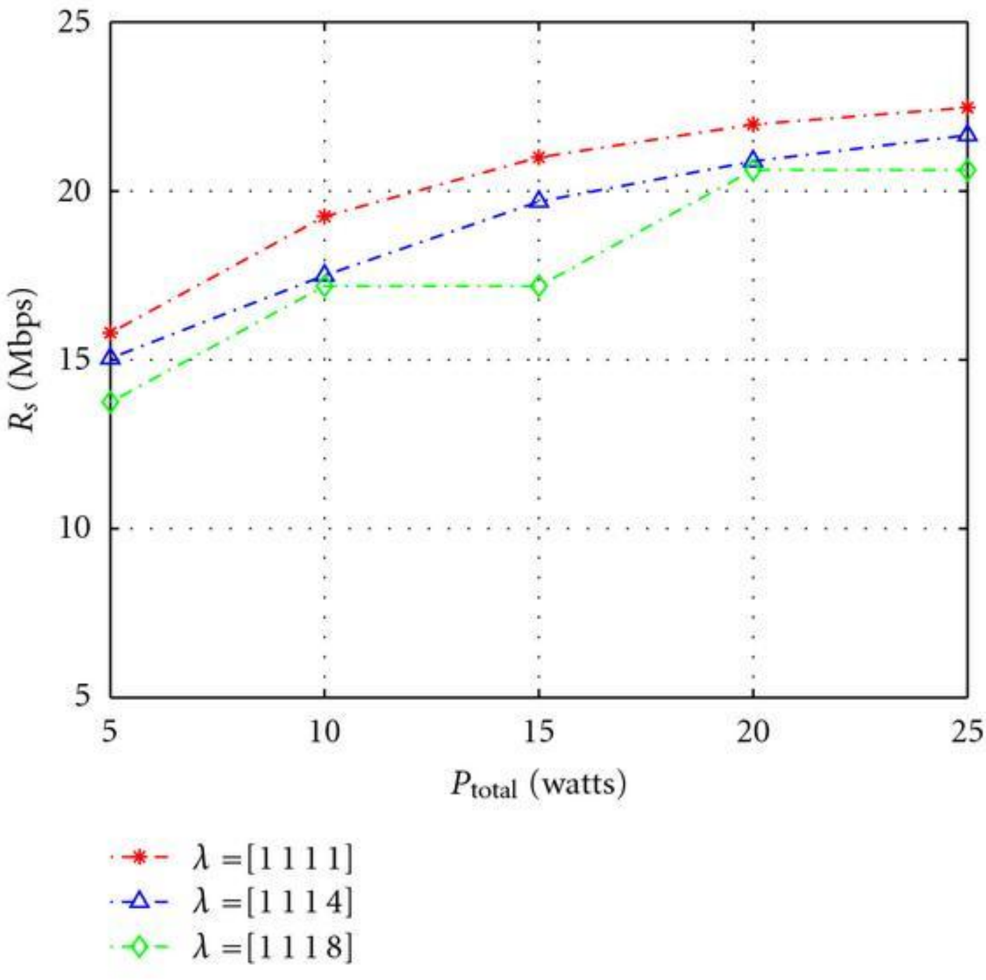

Figure 13.Average total CRU Rs Vs total CRU transmit power for ρ =0.9 with different λ

The above graph shows the three cases of different $\boldsymbol{\lambda}$ = [1 1 1 1], [1 1 1 4], [1 1 1 8] in the case ρ = 0.9 .the average total bit rate, R_s , as a function of the total CRU transmit power, P_{total} , I_{total}= 0.02 W, and a PU transmit power, P_m, of 5W. As expected, the average total bit rate increases with the maximum transmit power budgetP_{total}. It can be seen that R_s for $\boldsymbol{\lambda}$ = [1 1 1 1] is larger than for $\boldsymbol{\lambda}$ = [1 1 1 4], and R_s for $\boldsymbol{\lambda}$ = [1 1 1 4] is larger than for $\boldsymbol{\lambda}$ = [1 1 1 8]. When the bit rate requirements for CRUs become less uniform, R_s decreases due to a decrease in the benefits of user diversity. WithP_{total} = 15W, R_s increases by about 30% when $\boldsymbol{\lambda}$ changes from [1 1 1 8] to [1 1 1 1].

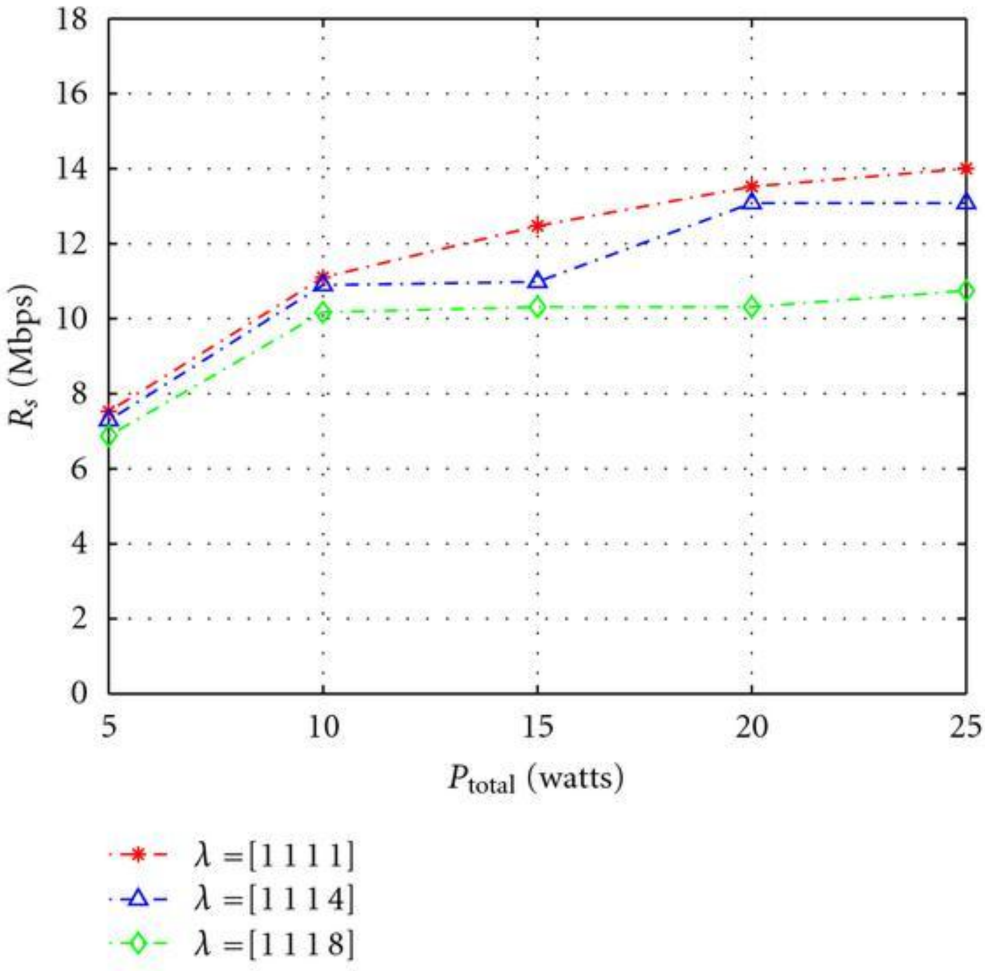

Figure 14. Average total CRU Rs Vs. total CRU transmit power for ρ =0.9 with different λ.

The above graph shows the three cases of different $\boldsymbol{\lambda}$ = [1 1 1 1], [1 1 1 4], [1 1 1 8] in the case ρ = 0.7 .the average total bit rate, R_s , as a function of the total CRU transmit power, P_{total} , I_{total}= 0.02 W, and a PU transmit power, P_m, of 5W. As expected, the average total bit rate increases with the maximum transmit power budgetP_{total}. It can be seen that R_s for $\boldsymbol{\lambda}$ = [1 1 1 1] is larger than for $\boldsymbol{\lambda}$ = [1 1 1 4], and R_s for $\boldsymbol{\lambda}$ = [1 1 1 4] is larger than for $\boldsymbol{\lambda}$ = [1 1 1 8]. When the bit rate requirements for CRUs become less uniform, R_s decreases due to a decrease in the benefits of user diversity. WithP_{total} = 15W, R_s increases by about 30% when $\boldsymbol{\lambda}$ changes from [1 1 1 8] to [1 1 1 1].

In order to get more insight of the impact of the other constraints on the average total bit rate R_s ,we study the variety of R_s under different maximum tolerable interference power , I_{total}.

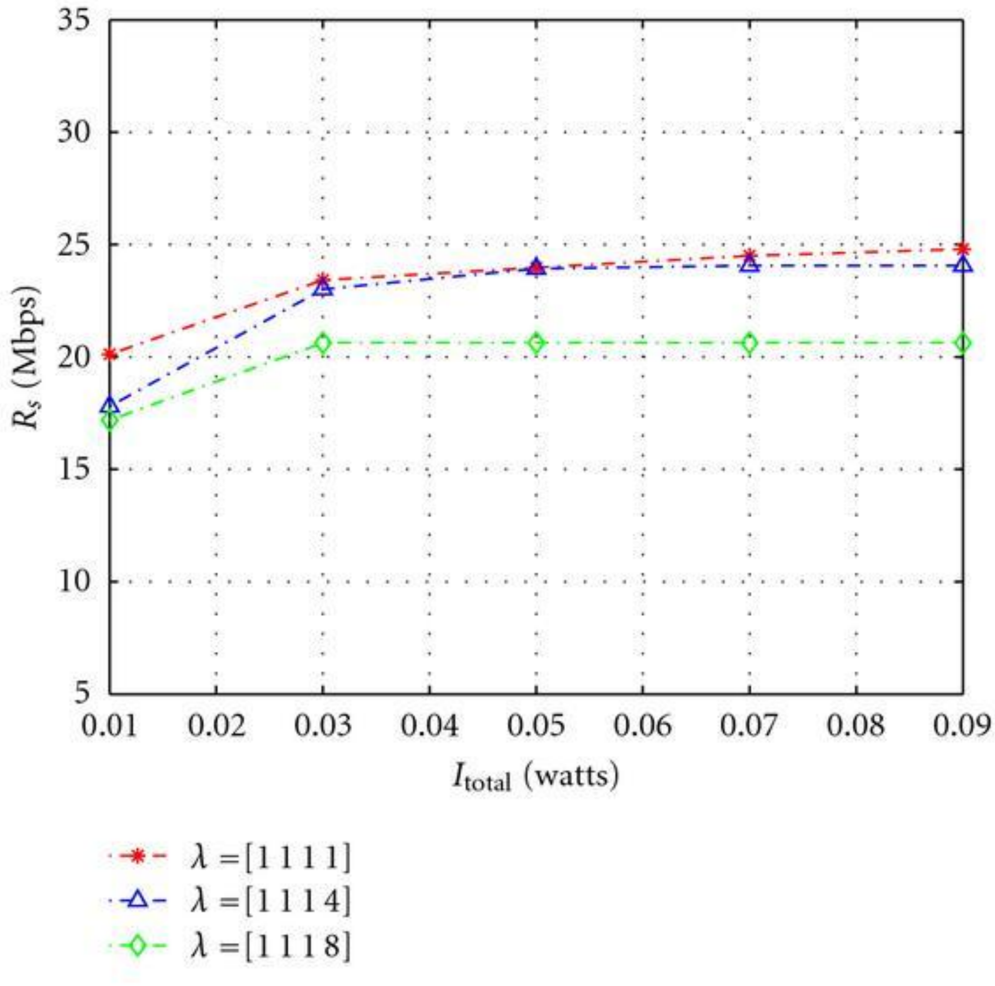

Figure 15. Average total CRU Rs Vs. maximum PU tolerable interference power total for ρ =0.9.

The average total bit rate, R_s , is plotted as a function of the maximum PU tolerable interference power, I_{total} , with P_{total} = 25 W and $P_m$of 5W for ρ = 0.9 in above graph respectively. As expected, R_s increases withI_{total} and decreases as the CRU bit rate requirements become less uniform. The $R_s$curves level off as I_{total}increases due to the fixed value of the total CRU transmit powerP_{total}.

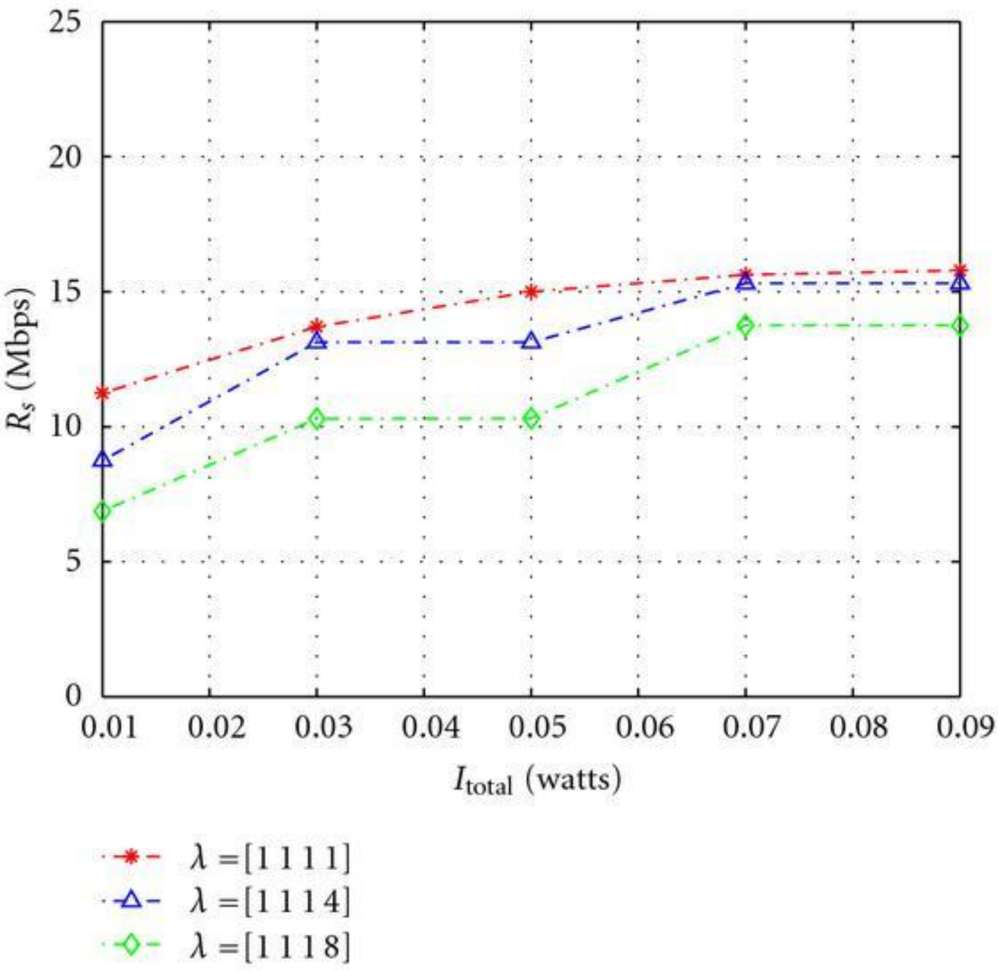

Figure 16.Average total CRU Rs Vs. maximum PU tolerable interference power total for ρ =0.7.

The average total bit rate, R_s , is plotted as a function of the maximum PU tolerable interference power, I_{total} , with P_{total} = 25 W and $P_m$of 5W for ρ = 0.7 in above graph respectively. As expected, R_s increases withI_{total} and decreases as the CRU bit rate requirements become less uniform. The $R_s$curves level off as I_{total}increases due to the fixed value of the total CRU transmit powerP_{total}.

Chapter 5

CONCLUSION & FUTURE WORK

5.1. Conclusion:

We have studied the subcarrier and power allocation problem with imperfect CSI in uplink cognitive radio systems. We have augmented the maximization formulation of this problem by taking into different constraints. We have proposed a two-step scheme with low computational complexity, in which subcarrier and power allocation are optimized separately. We have presented simulation results to show that when performing channel estimation with a larger number of training symbols, the sum capacity is largely increased. A realistic assumption is made on the special that all SUs have the same priority. Some algorithms were directly implemented from certain papers, which are the work done by esteemed engineers, and simply their behavior was studied. We used the system model where a primary band was operating side by side to the secondary band in a multi user system. The assumption that the transmitter always receives the channel state information perfectly is impractical for wireless systems .The system performance will degrade when the transmitter only has partial CSI. In order to maintain the system performance, an appropriate transmission schedule based on partial CSI is needed .However; the optimal resource allocation in MU-OFDM systems based on partial CSI is still an open issue. In this paper, we analyze the effects of partial channel state information on the resource allocation problem in MU-OFDM based cognitive radio systems. Based on obtained partial CSI at the transmitter, the average BER should satisfy the given BER target during transmission. As the function of average BER is to complex, we apply a Nakagami- m distribution to approximate the original function. A simple function, which is close to the original function, is derived. The resource allocation problem in MU-OFDM based cognitive radio systems is computational complex. In order make the problem tractable, we solve the problem into two steps. Firstly, we apply a simple SA algorithm for subcarrier allocation. Then we apply a simple at efficient memetic algorithm to solve the bits allocation problem. Different cases of partial CSI and bit rate requirements are studied .simulation show that partial CSI has great impact on the wireless transmission. In addition, due to user diversity, the total bit rate decreases when the data the data rate requirements become less uniform.

5.2. Future Work:

A realistic assumption is made on the spectral that all SUs have the same priority. For the Future work, we plan to study the general case that SUs experience different services that have individual rate and Quality of services constraints.

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